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Diagnóstico de fallos y optimización de la planificación en un marco de e-mantenimiento

Memoria que para optar al título de Doctor en Informática presenta

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Resumen

Para poder competir en cualquier nivel productivo o de operación, tanto a nivel nacional como internacional, es necesario que sistemas y equipos funcionen a niveles cada vez más altos de eficiencia, impensables hace un par de décadas. Mejoras en calidad, tiempos de respuesta cada vez más cortos y cambios continuos en la demanda de productos y servicios generan necesidades cada vez más altas de rendimiento en la operación y el mantenimiento.

Aunque es evidente que en los últimos años esta evolución ha conllevado grandes avances, y en especial se ha trabajado en el aumento de la disponibilidad y fiabilidad de la maquinaria, también es cierto que todavía se pueda recorrer un largo camino para llegar a una optimización completa en muchos ámbitos de aplicación.

El objetivo principal de esta memoria de tesis es demostrar el potencial de mejora que las técnicas y metodologías relacionadas con la analítica prescriptiva, pueden proporcionar en aplicaciones de mantenimiento industrial. Las tecnologías desarrolladas se pueden agrupar en tres ámbitos:

E-mantenimiento e interoperabilidad

Esta sección tiene especial relevancia para dar soporte a las estrategias relacionadas con el mantenimiento predictivo en continuo (*on-line*) de forma que puedan utilizarse las últimas tecnologías del mercado. Su continua reducción de costes ofrece claras oportunidades de mejora en los procesos de mantenimiento. Las tecnologías predictivas han evolucionado en estos últimos años y se están realizando avances importantes en aplicaciones mecánicas, térmicas, electromecánicas y más actualmente en sistemas eléctricos y electrónicos.

El e-mantenimiento está relacionado fundamentalmente con el desarrollo de plataformas colaborativas e inteligentes que permiten la integración de nuevos sensores, sistemas de comunicaciones, estándares y protocolos, conceptos, métodos de almacenamiento y análisis etc. que entran continuamente en nuestro abanico de posibilidades y nos ofrecen la posibilidad de seguir una tendencia de mejora en la optimización de activos y procesos, y en la interoperabilidad entre sistemas.

Diagnóstico de fallos

Las Redes Bayesianas (*Bayesian Networks* – BNs) junto con otras metodologías de recogida de información utilizadas en ingeniería nos ofrecen la posibilidad de

automatizar la tarea de diagnóstico y predicción de fallos. Las técnicas de aprendizaje automático se utilizan ampliamente con el mismo propósito, pero tienen el inconveniente de que necesitan un amplio abanico de datos para poder realzar un modelo fiable, y aun así existe riesgo de excesivo acoplamiento al sistema con el que se realiza las pruebas.

De todas formas, estas técnicas están más enfocadas a la detección de fallos específicos, mientras que el propósito de esta sección, en consonancia con el resto del proyecto de tesis no está centrado tanto en la resolución de un problema concreto, si no en la metodología que hay que tener en cuenta y las acciones que hay que llevar a cabo para realizar un buen sistema de diagnóstico en ausencia o escasez de datos, que es lo que ocurre en numerosas ocasiones.

Simulación de estrategias y optimización de la planificación

El objetivo principal de esta sección es centrarse en tecnologías que permitan optimizar las estrategias de mantenimiento, ya sea con diseños más fiables o mediante la mejora en las decisiones de mantenimiento. El análisis de coste-efectividad es clave porque es la forma de indicar si cualquier beneficio o ventaja competitiva se puede lograr mediante el uso de estrategias adecuadas de mantenimiento, especialmente con una orientación al mantenimiento predictivo. El uso de simulaciones coste-efectividad en este ámbito ayuda a la toma de decisiones a la hora de seleccionar una estrategia de mantenimiento adecuada para el activo.

Además, mediante el uso de algoritmos de optimización logramos mejorar la planificación del mantenimiento, reduciendo los tiempos y costes para realizar las tareas en un parque de activos. Durante el proyecto de tesis se ha desarrollado un algoritmo multiobjetivo basado en el uso del algoritmo de estimación de distribuciones (*Estimation of Distribution Algorithm* – EDA) para la optimización de los planes de mantenimiento. El concepto de analítica prescriptiva se hace plenamente patente en esta sección en base a la combinación de acciones predictivas (ej. predecir un fallo) simulación del coste-beneficio de diferentes decisiones relacionadas (ej. diferentes opciones de mantenimiento) y la búsqueda de la mejor decisión (o del conjunto de decisiones para un parque de activos).

Abstract

Systems and equipment must operate at increasingly higher levels of efficiency to compete at any production or operational level, nationally or internationally, not being possible a couple of decades ago. Improvements in quality, shorter response times and continuous changes in the demand for products and services generate higher performance needs in operation and maintenance.

Although in recent years this evolution has led to great advances, and research has been done to increase the availability and reliability of machinery, there is a long way to reach a complete optimization in many fields of application.

The main objective of this research work is to demonstrate the potential for improvement that techniques and methodologies related to prescriptive analytics can provide in industrial maintenance applications. The technologies developed can be grouped into three areas:

E-maintenance and interoperability

This section is particularly relevant to support strategies related to continuous predictive maintenance (on-line) using the latest technologies on the market. The continuous cost reduction provides clear opportunities for improvement in maintenance processes. Predictive technologies have evolved in recent years and important advances are being made in mechanical, thermal, electromechanical applications and more currently in electrical and electronic systems.

E-maintenance is fundamentally related to the development of collaborative and intelligent platforms that allow the integration of new smart sensors, communications systems, standards and protocols, concepts, storage and analysis methods, etc. that improve our range of possibilities and offer us the possibility of following a trend in the optimization of assets and processes, and interoperability among systems.

Fault diagnosis

The Bayesian Networks together with other information capture methodologies used in engineering provides automation of diagnosis and prediction of failures. Machine learning techniques are widely used for the same purpose, but they have the disadvantage that they need a wide range of data to enhance a reliable model, and still there is a risk of excessive coupling to the system with which the tests are performed.

In any case, machine learning techniques are more focused on the detection of specific failures, while the purpose of this section, like the rest of the thesis project, is not focused on solving a specific problem, but rather on the methodology that must be taken into account and the steps to follow to design a diagnostic system in the absence or scarcity of data, which happens many times.

Simulation of strategies and planning optimization

The main objective of this section is to focus on technologies that allow optimizing maintenance strategies, either with more reliable designs or by improving maintenance decisions. Cost-effectiveness analysis is key because indicates if any benefit or competitive advantage can be achieved using an adequate maintenance strategy, especially with a predictive maintenance target. The use of cost-effectiveness simulations in this area helps decision-making when selecting a suitable maintenance strategy for the asset.

In addition, by using optimization algorithms we can improve maintenance planning, reducing the time and costs to perform the tasks in an asset fleet. During the thesis project, a multi-objective algorithm was developed based on the use of an Estimation of Distribution Algorithm (EDA) to optimize maintenance plans. The concept of prescriptive analytics is fully evident in this section based on the combination of predictive actions (e.g. Failure prediction), simulation of the cost-benefit of different related decisions (e.g. different maintenance options) and the search for the best decision (or the set of decisions for an asset fleet).

Agradecimientos

En un principio tenía pensado leer unas cuantas secciones de agradecimiento de diferentes tesis para inspirarme en el uso de bonitas palabras y frases, estructura, longitud, etc., como si de un método de investigación se tratara. Pero no creo que sea la mejor manera de dar las gracias, puesto que, para dar bien las gracias, hay que hacerlo de forma espontánea y sincera. Así que he decido improvisar sobre la marcha, a ver que tal me sale.

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Trataré de hacerle honor tal y como hiciste en vida, y aunque has dejado el listón muy alto, intentaré estar a tu nivel.

Contenido

Índice de Figuras

Índice de Tablas

Parte I
Descripción del trabajo

1 Introducción

1.1 Antecedentes y Motivación

Los avances que se están viviendo en las últimas décadas en diferentes campos industriales y de servicios se basan en parte en el correcto rendimiento de los activos asociados, sin interrupciones no programadas o fallos inesperados. En este contexto, el creciente interés en la seguridad, la mayor calidad, la mejor sostenibilidad y la conservación de los bienes, junto con la presión para aumentar la eficiencia, inciden a su vez en la importancia del mantenimiento de los sistemas para garantizar un rendimiento óptimo de la maquinaria durante su máxima vida útil. Esta situación empuja a los gestores de mantenimiento hacia estrategias de mantenimiento preventivas (como por ejemplo el reemplazo, el reajuste periódico, etc.) en donde sobresalen, gracias al soporte tecnológico, estrategias de mantenimiento preventivo basadas en la evaluación automática de la condición de los activos.

El **mantenimiento basado en la condición** [Rao, 1996] tiene en cuenta el estado de operación del sistema mediante inspecciones periódicas que permiten detectar, diagnosticar y planificar una acción que permita corregir de forma anticipada una degradación del activo o un mal funcionamiento realizando las operaciones de mantenimiento mínimas para devolver al activo a su estado de funcionamiento correcto, anticipándose a situaciones de fallo más peligrosas. Este mantenimiento se puede implementar de varias maneras. Por un lado, se puede realizar manualmente, fuera de línea, en procedimientos también denominados inspecciones no destructivas, que se llevan a cabo periódicamente. Durante las inspecciones un operador con suficiente experiencia necesita acceder al equipo inspeccionado y realizar las mediciones requeridas. El análisis e interpretación de los datos puede tomar segundos o días, dependiendo de la automatización alcanzada. Por otro lado, el mantenimiento se puede aplicar en línea con mediciones y muestreos que generan automáticamente un conjunto de datos. Se puede enviar a un sistema de procesamiento separado físicamente del elemento monitoreado (análisis remoto), o también se puede analizar localmente a través de sistemas de software integrados. Finalmente, la información generada (tanto en línea como manual) puede ser de nuevo procesada, y aquí de nuevo es interesante poder contar con la inteligencia necesaria para realizar el diagnóstico y la toma de decisiones.

A medida que aumenta la presión para una gestión más eficiente de los activos, también se da impulso a la búsqueda de formas confiables y rentables de monitorización de la condición. En esta búsqueda **la automatización** es clave, para limitar tanto como sea posible los procesos de inspección manual, de reemplazo o de reparación de activos que están en buen estado, para minimizar costes y asegurar el mantenimiento y operación eficiente de los activos.

Sin embargo, existen todavía muchos aspectos que hay que trabajar para lograr sistemas automatizados. Por ejemplo, implica la necesidad de almacenar y procesar de manera adecuada todas las señales potencialmente útiles que pueden extraerse del sistema. Y la necesidad de dar un soporte robusto y fiable a lo largo del tiempo al mantenedor de activos para su toma de decisiones.

1.2 Tecnologías de soporte para el e-mantenimiento– Objetivos y marco de investigación

Este proyecto de tesis se centra en la investigación en algoritmos y plataformas que permitan solucionar los problemas a los que se enfrenta la aplicación eficiente del mantenimiento basado en condición. Y para llevar a cabo este propósito se propone el uso de tecnologías relacionadas con la Inteligencia Artificial, capaces de adaptarse y aprender de los datos existentes, pero también de tener en cuenta el conocimiento y la experiencia que no está en los datos, sino en los expertos, en la empresa o en los operadores. Este objetivo se complementa con la necesidad de disponer de una plataforma capaz de gestionar de manera ágil la inserción tanto de datos provenientes de múltiples fuentes como de los algoritmos adecuados.

Este proyecto de tesis comienza su desarrollo hace más de 15 años, cuando se comienza a entender que la aplicación de algoritmos y técnicas de Inteligencia Artificial pueden facilitar la implantación de estrategias de monitorización de la condición que permitan la automatización de la toma de decisiones en base a dicha condición [Arnaiz & Gilabert, 2004], y se ha enfocado en investigar las tecnologías que dan soporte a este tipo de procesos de mantenimiento avanzados basados en la monitorización de la condición.

Las líneas de investigación han coexistido en el tiempo, enlazadas en muchos casos con proyectos de investigación concretos (ver sección 1.7), y se ha orientado a tres áreas de investigación que confluyen en dar un soporte de 'inteligencia' al desarrollo del mantenimiento basado en condición.

En este trabajo se ha abordado en primer lugar el área relacionada con la búsqueda de una plataforma de gestión adecuada para adquirir los datos necesarios para realizar el mantenimiento avanzado, teniendo también en cuenta la necesidad de disponer de sistemas distribuidos y semiautomatizados de análisis de estos datos y de toma de decisiones. En concreto, este proyecto de tesis se enfoca en proporcionar soporte y ayuda en el diseño de un marco conceptual de **e-mantenimiento**, que permita incluir inteligencia para esta automatización.

Existe también un desarrollo importante coetáneo con el anterior, para automatizar el análisis de la información adquirida y almacenada en las plataformas de e-mantenimiento. En concreto, este trabajo propone la identificación de anomalías y el diagnóstico de fallos por medio de la aplicación de tecnologías de Inteligencia Artificial que pueden tener en cuenta tanto el conocimiento experto existente a-priori como los datos que se van adquiriendo a partir del uso de estas tecnologías, como es el caso de la utilización las de Redes Bayesianas.

Finalmente, existe una última línea de investigación más reciente que aparece en el momento en que las estrategias de mantenimiento avanzado, como por ejemplo las relativas a la monitorización de la condición, comienzan a ser consideradas alternativas viables para parte del trabajo de mantenimiento, alejándose de esquemas de mantenimiento preprogramados y expanden las opciones de mantenimiento asociadas a un parque de activos. En este momento es necesario considerar cómo realizar una optimización de las actividades teniendo en cuenta las diferentes opciones existentes. De nuevo aquí el objetivo es el uso de técnicas híbridas de Inteligencia Artificial también como parte de esta optimización.

1.3 E-mantenimiento. Plataforma colaborativa para el desarrollo de tecnologías inteligentes

El e-mantenimiento [Muller et al., 2008] es un concepto que trata de integrar una serie de principios dentro de la gestión del mantenimiento: la posibilidad de actuar de manera remota y predictiva; la sincronización de información y de sistemas, que permiten no sólo compartir datos e información sino también inteligencia entre los diferentes actores del mantenimiento; y finalmente la colaboración (entre mantenimiento y operación, entre humanos y autómatas, entre experiencia y datos).

Este concepto emerge a partir de 2 cambios: por un lado, las nuevas tecnologías que abarcan diferentes medios de adquirir y comunicar la información a través de

Internet, incluyendo desde sensores y comunicaciones inalámbricas hasta componentes móviles [Arnaiz et al., 2006], y por otro lado la necesidad de mejorar la eficiencia del negocio, integrando servicios que incluyan desde procesos tradicionales de mantenimiento hasta nuevos servicios relacionados con las posibilidades de realizar monitorización y predicción de condición [Ferreiro & Arnaiz, 2008], [Lee et al., 2006].

Aunque existen otros conceptos similares (telemantenimiento, mantenimiento inteligente, etc.) este es quizás el más claro en permitir visualizar las necesidades que una plataforma necesita cubrir para que pueda dar soporte a la inteligencia asociada a un sistema de mantenimiento basado en la condición (*Condition Based Maintenance* – CBM).

El desarrollo del e-mantenimiento se ha estructurado en base a diferentes líneas de trabajo, que en cierto modo se solapan [Muller et al., 2008]: la búsqueda de estándares y protocolos que faciliten la interoperabilidad de datos e información; el diseño de plataformas flexibles y colaborativas; y el diseño y desarrollo de algoritmos inteligentes que puedan operar dentro de dichas plataformas.

La búsqueda de estándares adecuados es muy amplia debido a los diversos sistemas que pueden requerir cierta interoperabilidad (sistemas productivos, cadena de suministro, etc.). Sin embargo, si nos centramos en los estándares que facilitan la interpretación de los datos y el desarrollo de funcionalidad relacionada con sistemas de mantenimiento predictivos o basados en la condición, destacan la norma ISO-13374 [ISO, 2012], junto con el esfuerzo normativo realizado por la asociación MIMOSA[1] a través, sobre todo, de la especificación OSA-CBM (*Open System Architecture for Condition Based Maintenance*) anticipada ya en [Lebold, 2002].

Esta base normativa es utilizada en trabajos como el realizado en [Monnin et al., 2011] con la herramienta KASEM, y el de [Guillen et al., 2016], destacando

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[1] MIMOSA: Open Standards for Physical Asset Management - https://www.mimosa.org/

recientemente el trabajo realizado alrededor del proyecto MANTIS[2] [Albano et al., 2019] en donde la arquitectura de e-mantenimiento es revisada teniendo en cuenta la necesidad de incorporar nuevos elementos, no sólo relacionados con la información que puede llegar a través de la internet 'industrial' de las cosas (*Industrial Internet of Things* – IIoT) sino también con sistemas ciber físicos (*Cyber Physical Systems* – CPSs) con capacidades de actuación semindependientes (Ver Figura 1). En este contexto, la plataforma es dividida en tres niveles que permiten una mayor flexibilidad en la conectividad tanto con los CPS (en el nivel nodo/'*edge*') como con todo tipo de aplicaciones empresariales (en el nivel 'empresarial') [Hegedüs et al., 2018].

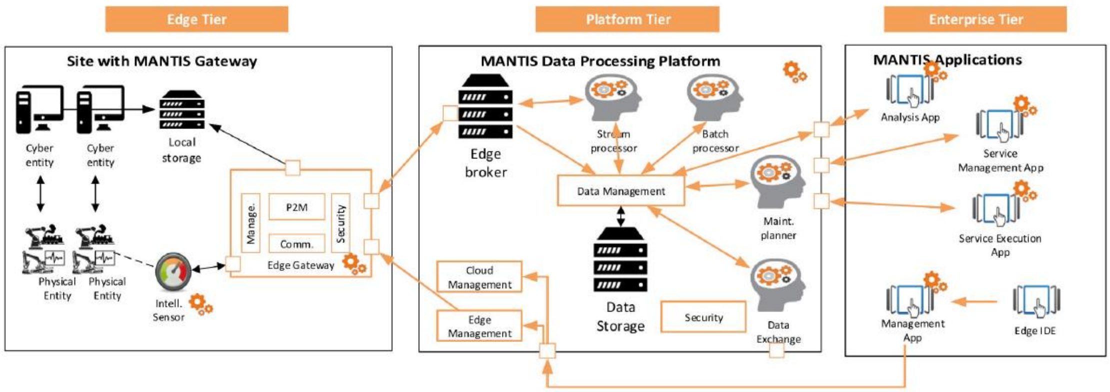

Figura 1. Arquitectura de referencia de MANTIS [Hegedus et al., 2018]

Mientras que los otros niveles, especialmente a nivel nodo, incluyen diferentes protocolos (ej. *OLE for Process Control Unified Architecture* – OPC UA) para garantizar la conectividad de todo el sistema, la parte central, (el nivel 'plataforma') sigue estando estructurada alrededor de las especificaciones MIMOSA, en donde multitud de actores construyen sus propios sistemas inteligentes. Por ejemplo, [Jantunen et al., 2019] usan esta misma base para desarrollar unos mecanismos de decisión sobre la necesidad de realizar acciones de mantenimiento basados en la información recopilada acerca del Retorno de la Inversión (*Return of Investment* – ROI)

[2] MANTIS: CPS based Proactive Collaborative Maintenance - https://cordis.europa.eu/project/id/662189

Por último, la incorporación de ontologías como palanca añadida de interoperabilidad, esta vez a nivel semántico, es otra vía de mejora que se ha sido trabajado por varios autores en el marco de su aplicabilidad en mantenimiento: [Teryizan & Kononenko, 2003] desarrollaron un primer trabajo conceptual que especifica un marco de servicios web aplicable al mundo industrial (*Enterprise Architecture Integration* – EAI), e incluye un diseño de alto nivel de una ontología capaz de integrar información de mantenimiento que se estructura en base a la interacción con dispositivos (monitorización y actuación), a sistemas de diagnóstico y a sistemas de decisión relacionados con la emisión de acciones y el aprendizaje continuo.

[Garetti et al., 2015] diseñan una ontología (*Manufacturing Systems Ontology* – MSO) que incluye diferentes clases y subclases generales (producto, componente, operador, …) para poder interoperar tanto con sistemas de producción y fabricación como con logística, teniendo a su vez en cuenta la necesidad de integración de dispositivos o CPSs. [Maleki et al., 2017] también se enfocan en la captura e interoperabilidad de los datos provenientes de sensores o CPSs, y en este caso si implementan una ontología completa capaz de capturar los datos de CBM (en este caso sobre los datos de vibración de un cabezal) facilitando el razonamiento sobre la señal adquirida. En todos estos casos se echa de menos el soporte de especificaciones y normativas a la hora de construir los modelos semánticos, quizás porque la amplitud del enfoque en el modelado de las ontologías (desde producción a logística) reduce las posibilidades de apoyarse en dichas especificaciones. Quienes sí lo logran son [Nuñez & Borsato, 2018], que despliegan un modelo detallado de ontología (OntoProg) para modelar la información de monitorización de condición y de las estrategias CBM y PHM (*Prognostic and Health Management*) asociadas, soportando este despliegue en el uso de la técnica del FMSA (*Failure Mode and Symptom Analysis*) como guía para la clasificación de modos de fallo, efectos, causas y síntomas, teniendo además como referencia diferentes estándares (empezando por el ISO 13359 [ISO 2011]) para asegurar la implementación más consistente y estándar posible (ver Figura 2).

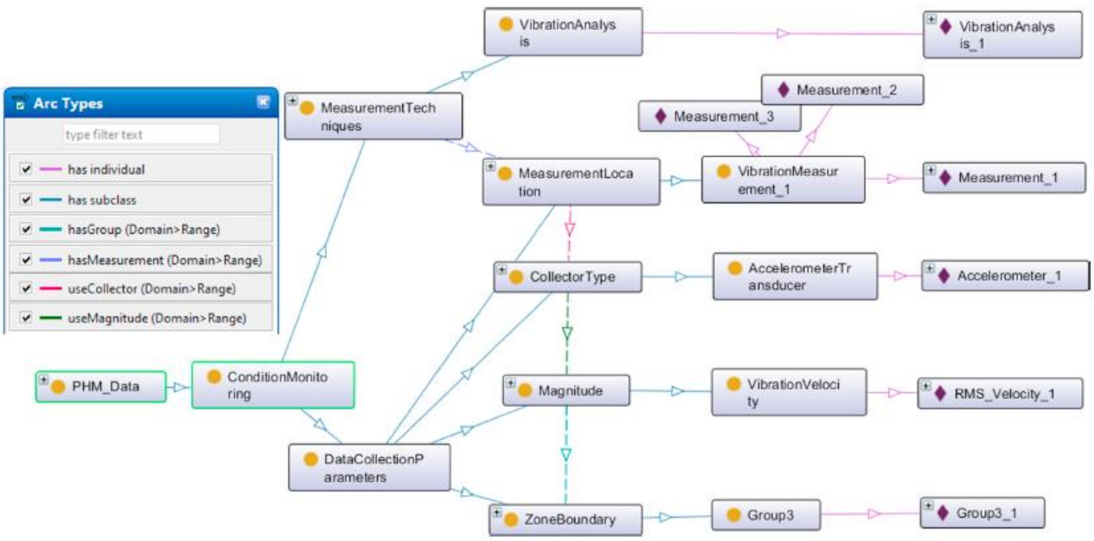

Figura 2. Instancias de la Subclase condition monitoring [Nuñez & Borsato, 2018]

Los trabajos más recientes incluyen los esfuerzos por formalizar las estructuras de representación de las acciones de mantenimiento a través de una notación más estandarizada (*Basic Formal Ontologies* - BFO), tal y como aparece en ROMAIN [Karray et al., 2019], o la inclusión de un modelizado semántico en plataformas ya existentes, como la mencionada anteriormente KASEM [Peysson et al., 2019], en donde la definición semántica de diferentes niveles constructivos (máquina, sistema, subsistema) y de descripción (técnico, de servicio, de operación y de rendimiento) facilitan el enlace entre la experiencia humana existente y su posible inclusión en sistemas de diagnóstico y soporte a decisiones. Finalmente, [Cao et al., 2020] proponen el uso de ontologías para estructurar un proceso de descubrimiento de conocimiento a partir de conjuntos de reglas existentes en identificación de anomalías que permita construir y refinar un sistema de soporte a decisiones en mantenimiento predictivo.

1.4 Sistemas de diagnóstico híbridos – combinación de experiencia y datos

El diagnóstico de fallos requiere de información de uso del sistema o componente y una estrategia de búsqueda de diagnóstico que permita identificar los síntomas observados y el conjunto conocido de posibles fallos. Además, se necesita un diagnóstico robusto para la detección de fallos incipientes para evitar las paradas de la planta [Volg et al., 2019]. Una técnica habitual para la detección de fallos considerando las incertidumbres es mediante la representación probabilística de las relaciones causales indeterminadas y la toma de decisiones bajo incertidumbre, por medio de una Red Bayesiana (*Bayesian Network* - BN).

Las Redes Bayesianas [Pearl, 2014] son modelos probabilísticos gráficos, en el que un nodo representa una variable o evento aleatorio y el borde dirigido conecta un padre con un hijo si existe una dependencia probabilística. Las capacidades de representación del conocimiento y toma de decisiones bajo incertidumbres de las BN han llevado a su aplicación en una variedad de problemas del mundo real [Weber et al., 2012][Yodo et al., 2016][Zhu et al., 2017].

Uno de los usos habituales en el ámbito del mantenimiento es el aislamiento de fallos en presencia de incertidumbres. Los fallos y síntomas se parametrizan usando variables de estado, lo que corresponde con los llamados nodos en una Red Bayesiana. A partir de la estructura, es necesario realizar un trabajo de reducción del conocimiento necesario tanto cualitativo como cuantitativo, por diferentes métodos ya sea usando conjuntos aproximados, ya sea por medio de modelos *Noisy-OR* / *MAX* [Wang et al., 2019]. Al adoptar el enfoque simplificado, los síntomas relacionados con fallos múltiples se desacoplan en fallos individuales, además de simplificarse la cantidad de probabilidades condicionales.

Otro enfoque eficiente es la integración precisa de un sistema CBM combinado con modelos de estrategia basados en simulación [Nielsen & Sørensen, 2018]. Usando Redes Bayesianas, la distribución de probabilidad para el tiempo de fallo y la distribución de probabilidad condicional para el tiempo de tareas de mantenimiento dado el tiempo de fallo, se estima teniendo en cuenta la estrategia de CBM, y son utilizadas por el modelo de estrategia basado en simulación para generar fallos y tareas de mantenimiento.

[Xiao et al., 2016] presenta primero las reglas de asociación en forma de Redes Bayesianas que se extraen de diferentes bases de datos de diferentes sistemas producto/servicios industriales, y se pueden usar para representar el conocimiento adquirido. Luego establece un marco de reutilización del conocimiento basado en la inferencia bayesiana, que se utiliza para apoyar la toma de decisiones relacionadas con las operaciones de mantenimiento. La metodología propuesta se aplica a un caso del mundo real en una empresa de fabricación de equipos agrícolas. Las Redes Bayesianas también se utilizan para la actualización de la fiabilidad, ya sea a través de inspecciones [Tran et al., 2020] o modelando la degradación de un elemento [Lee & Choi, 2020].

Las Redes Bayesianas dinámicas (*dynamic Bayesian Networks* – dBNs) son un tipo particular de BN que modelan estructuras de datos secuenciales o series temporales. [Nielsen et al., 2018] desarrolla dos modelos de decisión, ambos basados en Redes Bayesianas dinámicas para el modelado de deterioro. Presenta un marco computacional para la planificación basada en riesgos de inspecciones y reparaciones de componentes deteriorados. Se utilizan dos tipos distintos de reglas de decisión para modelar decisiones: reglas de decisión simples que dependen de constantes o variables observadas (por ejemplo, resultado de la inspección) y reglas de decisión avanzadas que dependen de variables encontradas utilizando la actualización bayesiana (por ejemplo, probabilidad de fallo).

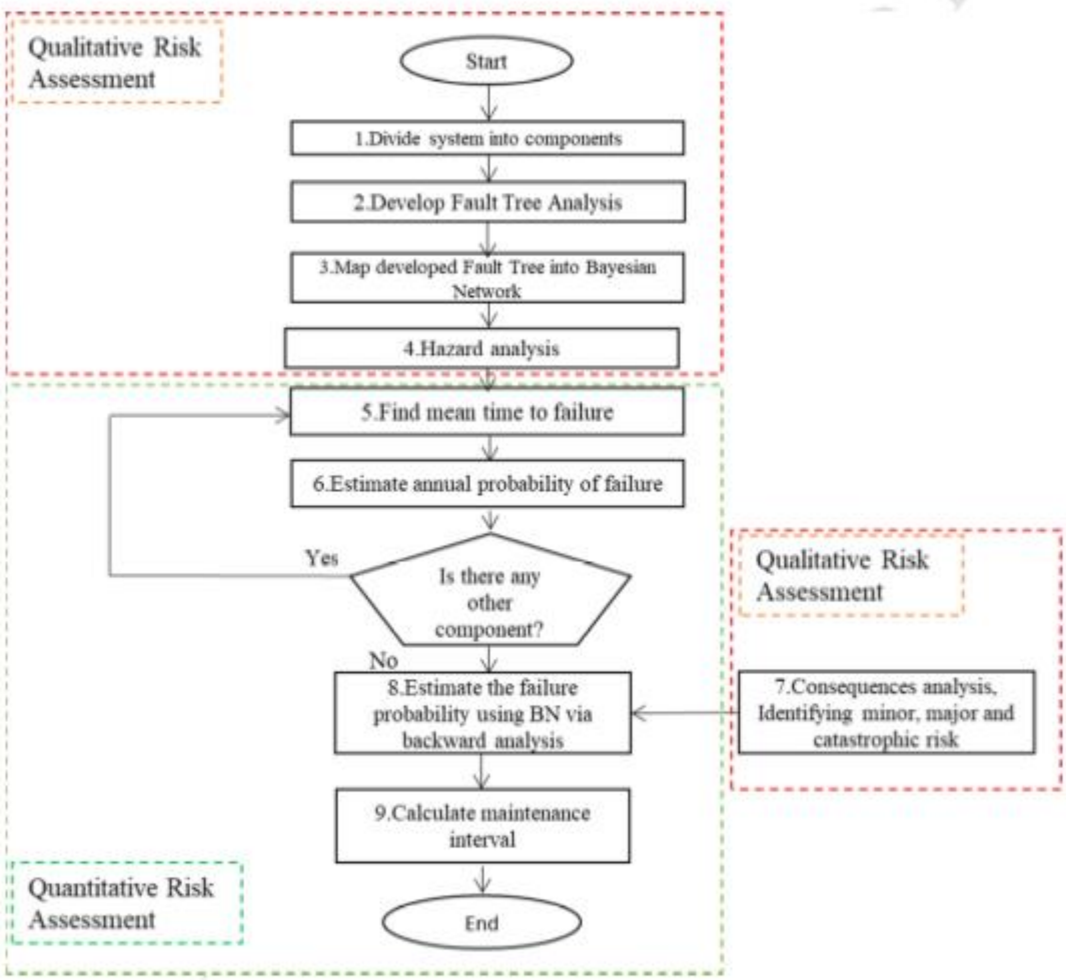

Figura 3. Metodología RBM propuesta por [Leoni et al., 2019]

En los últimos años se ha desarrollado la metodología de mantenimiento basado en riesgos (*Risk Based Maintenance* – RBM) que trata de realizar la planificación del mantenimiento basado en el análisis de riesgos minimizando la probabilidad de fallo del sistema y sus consecuencias (relacionadas con la seguridad, la economía y el medio ambiente) [Kahn & Haddara, 2003]. Esta metodología se usa en la actualidad para optimizar el mantenimiento en una planta de gas natural [Leoni et al., 2019], donde se aplica una Red Bayesiana para modelar el riesgo y la incertidumbre asociada. El método desarrollado ayuda a los administradores de activos a calcular el tiempo exacto de mantenimiento para cada componente de acuerdo con el nivel de riesgo (Ver Figura 3).

1.5 Analítica prescriptiva para la optimización del mantenimiento

El cambio en las estrategias de mantenimiento ha sido fomentado en los últimos años por el aumento de opciones y tecnologías en las diversas etapas del monitoreo de la condición (adquisición, transmisión y procesamiento de información), que están disminuyendo el coste de la inclusión de estas estrategias. Esto a su vez abre un abanico importante de opciones, tanto en las estrategias de mantenimiento generales de una empresa, como en la gestión y operación diaria de un parque de activos que es difícil realizar eficientemente de forma manual. Este proyecto propone abordar este problema de optimización también por medio de la inclusión de técnicas de Inteligencia Artificial, y más en concreto con técnicas relacionadas con la analítica prescriptiva.

La analítica prescriptiva se extiende más allá de la analítica predictiva al especificar tanto las acciones necesarias para lograr los resultados previstos como los efectos interrelacionados de cada decisión. Mientras que la analítica predictiva está relacionada con el análisis descriptivo y predictivo de los datos, la analítica prescriptiva añade una exploración del conjunto de acciones que pueden ser realizadas a partir del análisis predictivo, y realiza sugerencias a partir del impacto potencial de dichas acciones (Ver Figura 4). Por lo tanto, la analítica prescriptiva guía la toma de decisiones con el fin de encontrar una solución óptima y, aunque la decisión final depende siempre de la persona responsable, proporciona medios confiables para optimizar las necesidades del negocio y la resolución de problemas.

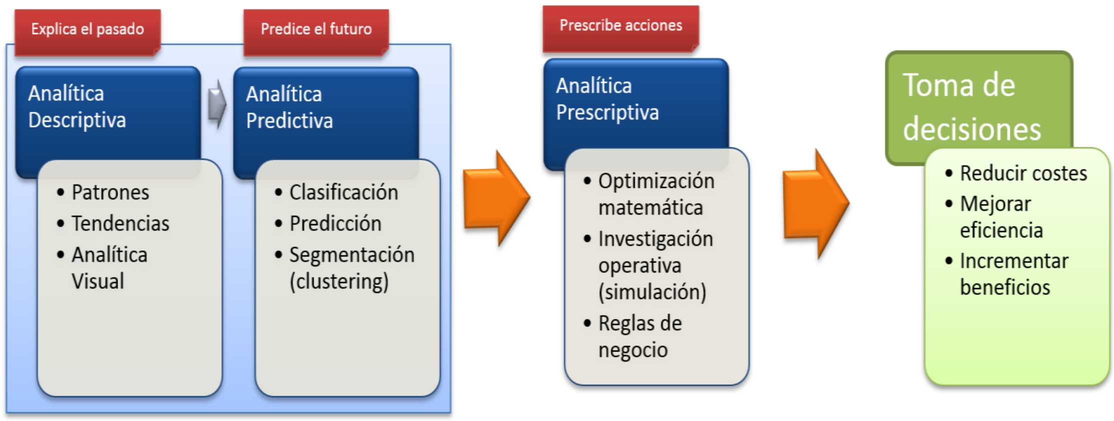

Figura 4. Analítica prescriptiva y su relación con descriptiva y predictiva, en la toma de decisiones

Estos problemas de optimización buscan encontrar el conjunto de parámetros que cumple cierto criterio que se quiere optimizar, maximizando o minimizando cierta función de evaluación *f(x)*. Existen diferentes formas de resolver estos problemas de optimización, en donde básicamente se pueden encontrar algoritmos que buscan en todo el espacio de soluciones, con el coste computacional y lentitud en encontrar una respuesta asociados, y algoritmos capaces de buscar caminos óptimos en el espacio de soluciones, ya sea a partir de heurísticos, o bien sea a partir de conceptos avanzados como la computación evolutiva.

Para solucionar este problema, [Pattison et al., 2016] presenta una arquitectura para realizar el mantenimiento centrado en la fiabilidad (*Reliability-Centered Maintenance* - RCM). El objetivo de esta arquitectura es ilustrar la integración de diferentes métodos matemáticos en el desarrollo de una solución para RCM, que posteriormente se implementa en una aplicación de energía eólica. Dentro de la solución presentada, la toma de decisiones se basa en las observaciones de los sensores instalados en las turbinas y del *Condition Monitoring* (CM) asociado que proporciona información de comportamiento anómalo. Posteriormente la fiabilidad y el modelado del mantenimiento (*Risk and Maintenance Modelling* - RMM) apoyan la toma de decisiones al proponer diferentes opciones de mantenimiento y, finalmente, la planificación genera una decisión casi óptima con respecto a la efectividad de los costes de mantenimiento general del parque eólico. La Figura 5 proporciona una ilustración de cómo los módulos asociados pueden integrarse desde una perspectiva de flujo de información para crear la solución y consta de seis pasos enumerados de alto nivel.

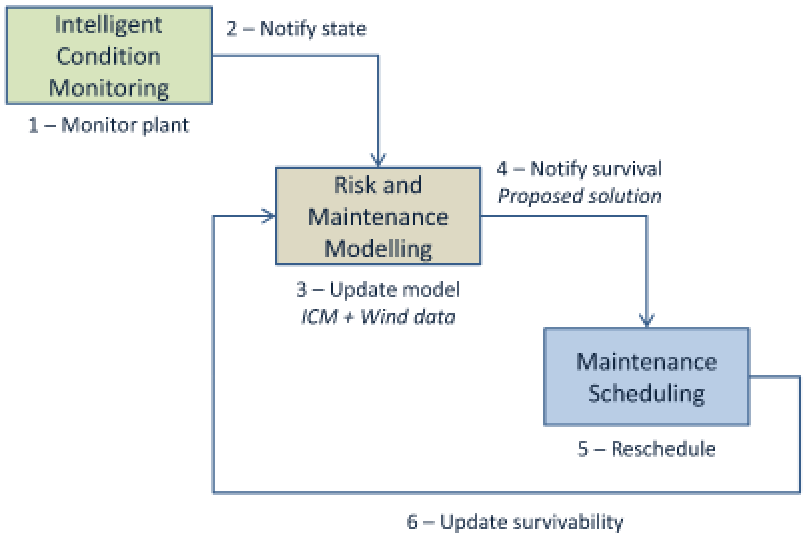

Figura 5. Flujo de información a alto nivel [Pattison, 2016]

En los últimos años, las metaheurísticas como los Algoritmos Genéticos (*Genetic Algorithms* – GAs), el enfriamiento simulado y la búsqueda tabú se han utilizado ampliamente junto con la simulación de los procesos de mantenimiento para mejorar la eficacia del procedimiento de búsqueda. Entre estos métodos de búsqueda guiada, la optimización de la simulación a través de GAs es un área de investigación bastante activa. Existen aplicaciones exitosas de este tipo en procesos tales como la programación; la disposición de una instalación; la planificación de una línea de ensamblaje; la gestión de una cadena de suministro; los sistemas Kanban; la selección de políticas de mantenimiento; y la gestión del inventario de repuestos [Shafiee & Sørensen, 2019][Zao et al., 2019].

La influencia de las políticas de mantenimiento en la política de aprovisionamiento de repuestos no puede ignorarse, ya que la necesidad de piezas de repuesto está directamente dictada por las políticas de mantenimiento. Teniendo en cuenta el hecho de que el mantenimiento preventivo está programado, la demanda de piezas de repuesto es predecible. Para un fallo de la máquina que requiere de una reparación no planificada, el desabastecimiento de piezas de repuesto hace que la producción se detenga, con costes significativos. Diferentes autores proponer soluciones a esta optimización, principalmente mediante el uso de algoritmos genéticos [Cai et al., 2017] u otras técnicas como las de *multi-echelon* [Wang et al., 2019b], voraz heurístico [Rahimi-Ghahroodi et al., 2019] o *Particle Swarm Optimization* [Karevan & Vasili, 2018].

A la hora de aplicar estos sistemas de optimización dentro de los procesos de mantenimiento, hay que tener en cuenta que los objetivos pueden ser variados, desde aumentar la vida útil del equipo, manteniendo al mismo tiempo la seguridad y la fiabilidad del sistema, hasta reducir costes identificando ineficiencias en las tareas de mantenimiento [Syan & Ramsoobag, 2019].

Este trabajo de investigación (capítulo 0) presenta como principal actividad en este campo el desarrollo de algoritmos capaces de optimizar los planes de mantenimiento. Para ello por un lado identifica y concreta procesos que merecen ser tratados como problemas de optimización (por ejemplo, el desarrollo de planes de mantenimiento) y por otro evalúa y desarrolla combinaciones de técnicas para conseguir los mejores resultados.

1.6 Unidad de Sistemas de Información Inteligentes de Tekniker

Las actividades de investigación descritas en esta memoria de tesis han sido realizadas en Tekniker, un centro tecnológico localizado en Éibar y constituido como Fundación privada sin ánimo de lucro, cuya misión es la de contribuir a incrementar la capacidad de innovación del tejido industrial. Las áreas de investigación de Tekniker incluyen Fabricación Avanzada, Ingeniería de superficies, Tecnología de la información y comunicación, e Ingeniería de producto. Por su cercanía al entorno, gran parte de su investigación se centra en máquina herramienta y fabricación, aunque también cubre otros sectores industriales como aeronáutica, agroalimentación, salud, energía e infraestructuras.

Dentro de Tekniker, el grupo de investigación de Sistemas de información inteligentes está compuesto por 23 personas, de las cuales 7 son doctores y 4 son doctorandos. La unidad se centra en el uso de tecnologías de hardware y software para el modelado y automatización de la supervisión y apoyo a la toma de decisiones para sistemas de procesos y gestión de activos. Esto implica el modelado de sistemas en los que se deben de tener en cuenta las características físicas, las tendencias y los parámetros de la condición, los patrones de datos y/o los conocimientos técnicos de los históricos. Durante el desarrollo de este trabajo de investigación, el autor ha crecido técnica y personalmente gracias al apoyo de este equipo de investigación.

La especialización del grupo de Sistemas de Información Inteligentes gira en torno a tres áreas:

1. El **análisis predictivo** basado en el uso de tecnologías de hardware y software para el modelado y automatización de la supervisión y sistemas de soporte a la decisión de procesos y gestión de activos. Las principales tecnologías que desarrollan son nuevos sistemas de sensores (para *condition monitoring*), técnicas de Inteligencia Artificial para el modelado flexible, automatización de soluciones, manejo de la incertidumbre y habilidades de autoaprendizaje, así como soluciones y estrategias de e-mantenimiento.

2. El desarrollo de las **capacidades de razonamiento** de los sistemas de soporte a la decisión a través del enriquecimiento de datos (contenido inteligente), la representación del conocimiento de dominio (ontologías), reglas de definición, y razonadores, todos ellos basados en las tecnologías y marcos semánticos. Las tecnologías que estamos aplicando actualmente tienen diferentes enfoques, la interacción natural entre robots y seres humanos, o la aplicación de semántica al modelado y análisis predictivo.

3. El **soporte en la nube a los sistemas ciber físicos** (CPSs), que se centra en la provisión de plataformas adecuadas para el conocimiento del contexto de las redes inteligentes de CPSs. Esto incluye la provisión de plataformas flexibles basadas en arquitecturas abiertas estándar para la interoperabilidad y escalabilidad de las soluciones para la adquisición de grandes volúmenes de datos y preprocesamiento. Del mismo modo, también se llevan a cabo la explotación de los datos y contenidos de información por medio de análisis predictivo y tecnologías semánticas.

1.7 Descripción general de los proyectos de investigación

Los proyectos descritos a continuación corresponden a las actividades realizadas en Tekniker y su línea de especialización de Analítica Predictiva. Las actividades de investigación presentadas en esta memoria se han desarrollado en el ámbito de estos proyectos, que se presentan en orden cronológico.

1.7.1 TATEM

- **Título**: Technologies and Techniques for new maintenance concepts.

- **Tipología**: Proyecto Integrado (IP), 6º Programa Marco de la comisión europea (FP6).

- **Periodo**: 2004-2009.
- **Consorcio**: Reunió a 57 empresas miembros de 12 países europeos, Israel y Australia. Entre los grandes nombres involucrados se incluyen GE Aviation System (líder), Airbus, Air France, Alenia, BAE Systems, Eurocopter, EADS, Thales, Safran y SR Technics.

Objetivos y resultados

El objetivo del proyecto TATEM era validar tecnologías y técnicas que se pueden utilizar para transferir el mantenimiento no programado al mantenimiento programado y proporcionar los medios para hacer que la tarea de mantenimiento sea más eficiente y efectiva (ver Figura 6). Las tecnologías y técnicas utilizadas son las siguientes:

- Nueva tecnología de sensores a bordo para recopilar datos de los sistemas de la aeronave (aviónica, utilidades, actuación, motores y estructuras).
- Técnicas de procesamiento de señales (Ej. lógica difusa, redes neuronales, razonamiento basado en modelos) que se pueden usar para convertir datos en información sobre el estado de los sistemas.
- Métodos de diagnóstico para identificar y localizar fallos y mal funcionamiento y así reducir el número de incidentes sin fallos encontrados.
- Métodos de pronóstico para apoyar las acciones de mantenimiento preventivo.
- Técnicas de apoyo a la decisión para generar información orientada a procesos.
- Tecnologías de interfaz humana para proporcionar al equipo de tierra información, datos y asesoramiento en el punto de trabajo.

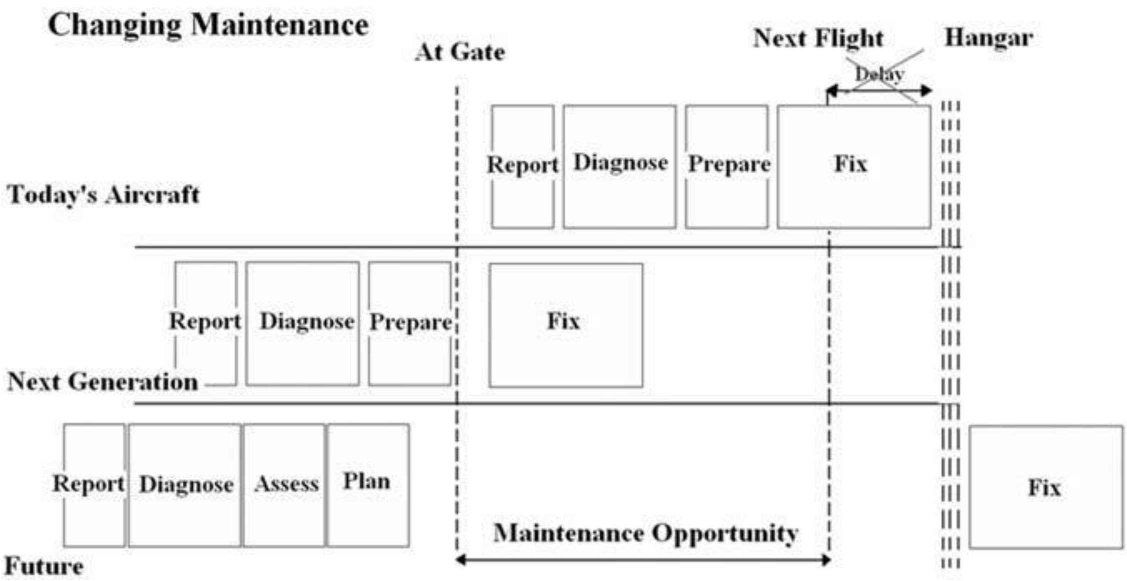

Figura 6. Fallos no detectados en una etapa temprana pueden causar retrasos en el siguiente vuelo

1.7.2 DYNAMITE

- **Título**: Dynamic decisions in maintenance.
- **Tipología**: Proyecto Integrado (IP), 6º Programa Marco de la comisión europea (FP6).
- **Periodo**: 2005-2009.
- **Consorcio**: VTT (líder), Tekniker, University of Sunderland, Centro Ricerche FIAT, Université Henri Poincaré, University of Manchester, Växjö University, Zenon, Volvo, Goratu, Martechnic, Wyselec, Engineering Statistical Services, Diagnostic Solutions, Prisma Electronics, IB Krates y Hydrox Pipeline.

Objetivos y resultados

El proyecto DYNAMITE (ver Figura 7) tenía varios objetivos relacionados con la mejora del proceso del mantenimiento en la industria, con empresas participantes como Volvo y Fiat. En particular, se potenciaron y adaptaron nuevas tecnologías para la inclusión de estrategias predictivas dentro de las actividades de mantenimiento en la industria. Entre las nuevas tecnologías destacan tanto aspectos hardware (microsensores, etiquetas inteligentes, sensores lubricación) como aspectos de la comunicación y de la información (comunicación inalámbrica, dispositivos móviles inteligentes, e-mantenimiento semántico, automatización del análisis coste-efectividad). Tekniker participó dentro del grupo principal de compañías del consorcio, con desarrollos tanto en hardware como en tecnologías de la información.

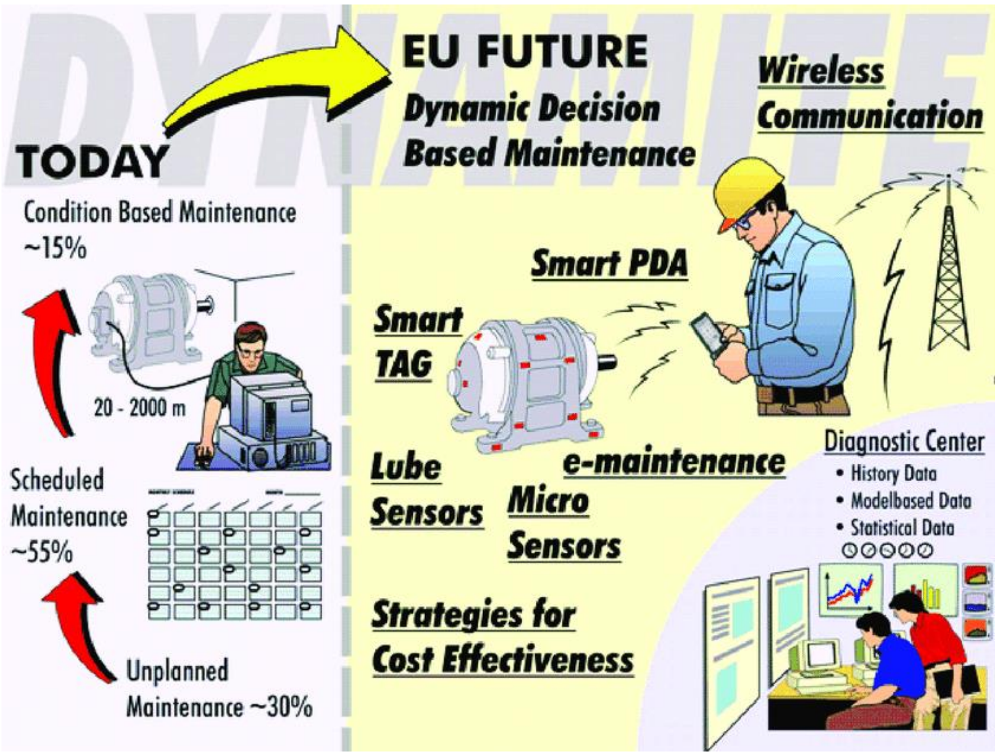

Figura 7. Decisiones dinámicas en mantenimiento

1.7.3 HEGEL

- **Título**: High Efficiency Polygeneration applications.
- **Tipología**: Programa TREND, 6º Programa Marco de la comisión europea (FP6).
- **Periodo**: 2006-2009.
- **Consorcio**: Centro Ricerche FIAT (líder), Tekniker, 2HEnergy, Energiprojekt, Politecnico di Torino, Ranotor, Repsol YPF, Universitat Rovira i Virgili, Energia Serveis y Noves Tecnologies, Untes y COGEN Europe.

Objetivos y resultados

El objetivo del proyecto, liderado por FIAT y con participación de Repsol, fue el desarrollo de sistemas de trigeneración usando diferentes tecnologías que mejoren la eficiencia energética de los sistemas actuales de cogeneración (ver Figura 8). Tekniker tenía como objetivo desarrollar un software de control y monitorización de estado de los trigeneradores de energía basados en motores de combustión interna y turbinas que usan entre otros, combustibles renovables. Entre las actividades realizadas destacó la implantación de un sistema de monitorización del estado en los componentes del trigenerador más propensos a fallos y pérdidas de eficiencia, basado principalmente en la combinación de las señales de eficiencia de operación (voltaje, intensidad, eficiencia) junto con información de vibraciones.

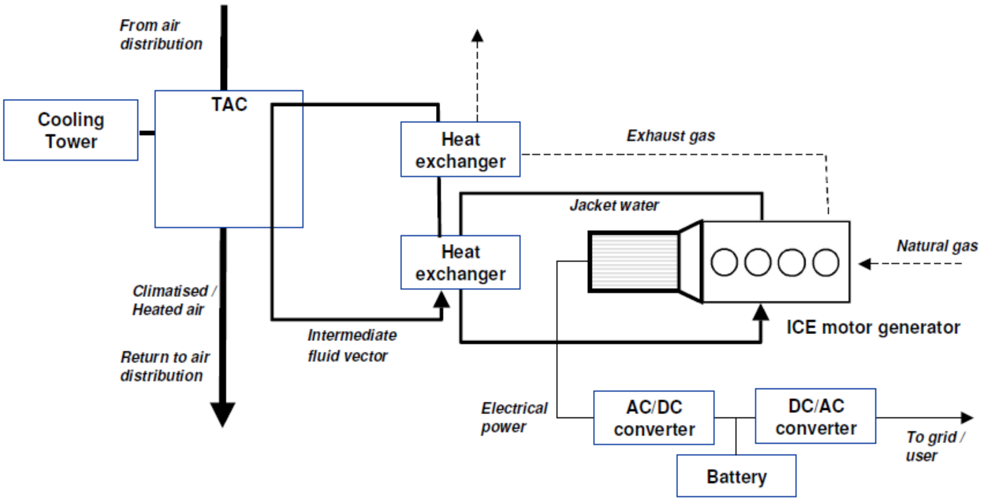

Figura 8. Diagrama del sistema de trigeneración

1.7.4 POSSEIDON

- **Título**: Progressive oil sensor systems for extended identification on-line.
- **Tipología**: STREP Transporte, 6º Programa Marco de la comisión europea (FP6).
- **Periodo**: 2007-2010.

- **Consorcio**: Martechnic (Líder), Tekniker, IB Krates, Institut für Mikrotechnik Mainz, BP Marine, Rina, Oelcheck y University of Sunderland.

Objetivos y resultados

Este proyecto persigue incorporar a los buques la filosofía del "*condition monitoring*" (mantenimiento predictivo), dotándoles de los elementos de sensorización necesarios. El objetivo que la lubricación de los motores marinos cuente con un sistema completo de mantenimiento "on-line" capaz de ahorrar lubricante y de alargar la vida útil de los componentes y del motor en su conjunto. De esta forma se desarrollaron tres sensores específicos: uno primero de infrarrojos, destinado a seguir la calidad del aceite, un segundo orientado a la determinación de impurezas (partículas), y el tercero para medir la evolución de la viscosidad del aceite. Además, fue desarrollado un sistema de diagnóstico basad en el uso de una Red Bayesiana que diagnosticaba lo fallos de los motores diésel a partir de la información de dichos sensores (Ver Figura 9).

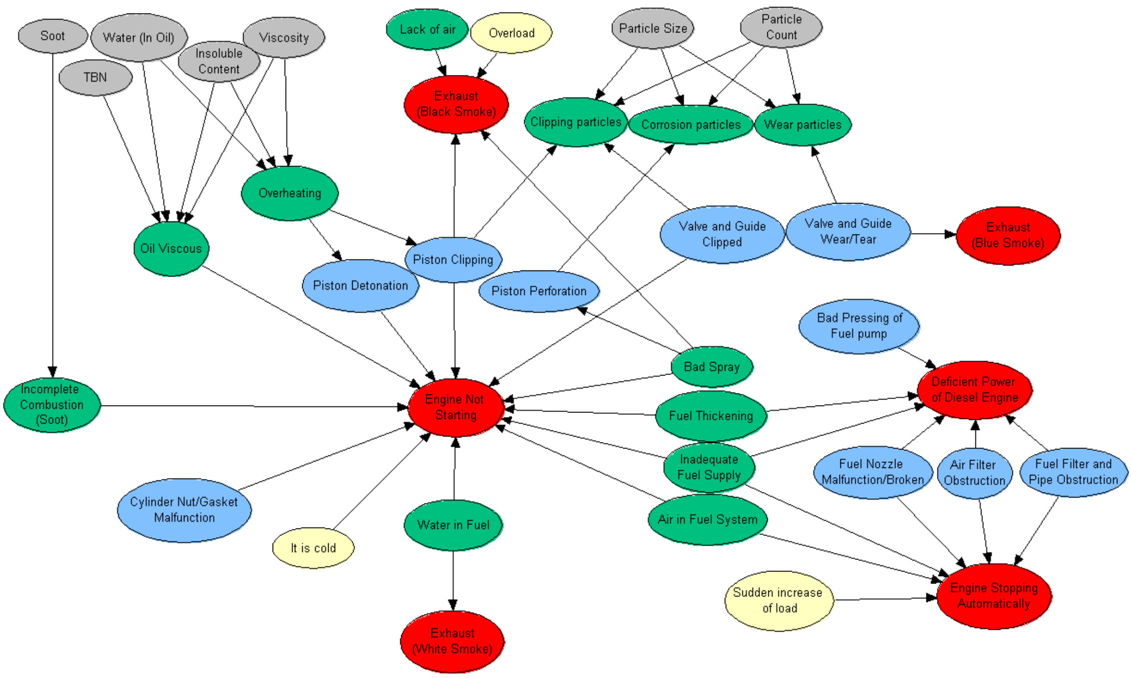

Figura 9. Red Bayesiana para diagnóstico de fallos en motores marinos diésel

1.7.5 PROSAVE2

- **Título**: Proyecto de investigación en sistemas avanzados para un avión más eco-eficiente.

- **Tipología**: Subprograma de apoyo a Consorcios Estratégicos Nacionales de Investigación Técnica (CENIT), CDTI.
- **Periodo**: 2010-2013.
- **Consorcio**: CESA (líder), Sisteplant, Tekniker, Aerlyper, Aernnova, Airbus, ALME, Cegasa, EADS, GreenPower, Hynergreen, Krafft, Maprotechnologies, Naturgas, Ramem, Temai, TTT, VTI y JMP Ingenieros.

Objetivos y resultados

El objetivo principal fue el desarrollo de tecnologías para soporte de mantenimiento y operación, y su adaptación dentro de los sistemas (actuadores, trenes de aterrizaje, etc.) permitiendo el desempeño eficiente de estas actividades, una reducción de costes económicos y ambientales, y también mejorando la seguridad en posibles fallos humanos (ver Figura 10).

Tekniker en colaboración con Sisteplant, participó en los siguientes resultados:

- Definición de un modelo estándar de datos basado en la gestión de mantenimiento y configuración
- Revisión de las mejores tecnologías para la identificación de componentes, captura y almacenamiento de información
- Diseño y desarrollo de una plataforma distribuida y algoritmos de optimización para la operación de mantenimiento.

Figura 10. Objetivos y tecnologías del Proyecto PROSAVE2

1.7.6 MANTIS

- **Título**: Cyber Physical System based Proactive Collaborative Maintenance.
- **Tipología**: ECSEL-RIA, programa Horizon 2020 financiado por la Union Europea.
- **Periodo**: 2015-2018.
- **Consorcio**: 47 socios de 12 paises europeos, incluyendo Mondragon Goi Eskola Politeknikoa, Tekniker, Ikerlan, Fagor, Acciona, Aalborg Universitet, Vestas, Philips, Bosch y Liebherr.

Objetivos y resultados

El objetivo general del proyecto MANTIS fue crear un marco basado en sistemas ciberfísicos que habilita un ecosistema cooperativo de mantenimiento y concebido como un sistema de conocimiento integrado e inteligente que incluye la monitorización de datos, la comunicación y el análisis avanzado con capacidades de autoaprendizaje (ver Figura 11). De esta forma es posible reducir los costes y el tiempo de las tareas de mantenimiento, mejorar la calidad del servicio, las condiciones de trabajo de mano de obra y el rendimiento de mantenimiento.

Tekniker participó en el desarrollo de una plataforma de mantenimiento proactivo basada en Sistemas Ciberfísicos que permite estimar el rendimiento futuro, predecir y prevenir fallos inminentes y programar mantenimiento proactivo.

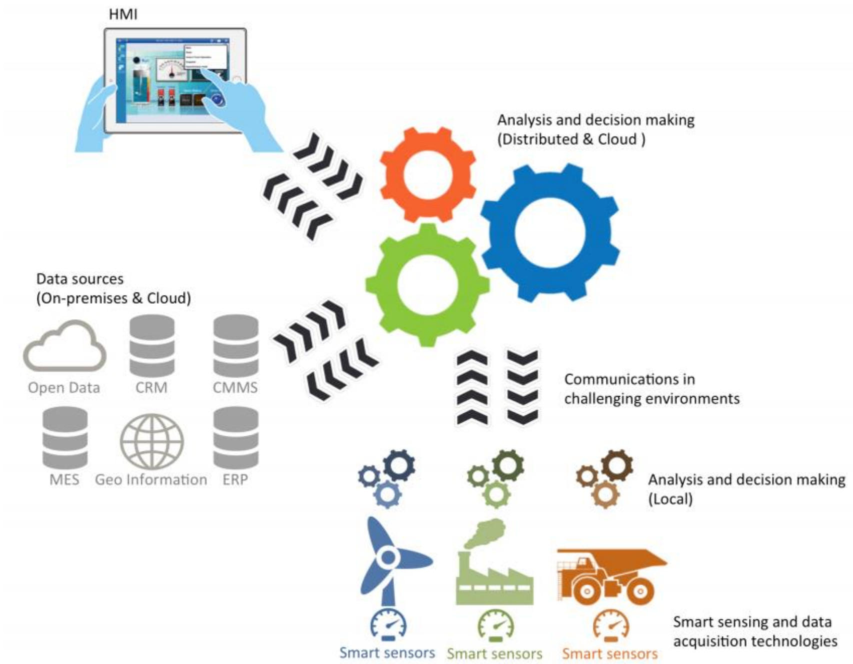

Figura 11. Ecosistema colaborativo en el Proyecto MANTIS

1.7.7 MAINWIND+

- **Título**: Nuevas tecnologías y soluciones para la optimización de operación y mantenimiento de parques eólicos
- **Tipología**: Proyectos de investigación industrial y de Desarrollo experimental en sectores estratégicos (HAZITEK), Gobierno Vasco.
- **Periodo**: 2016-2018
- **Consorcio**: Ingeteam, Tekniker, Sisteplant, NEM Solutions, Matz-Erreka, Glual, Laulagun, Renogear, Atten2, Fegemu, Hispavista, Ceit, Ikerlan, Vicomtech, Tecnalia y Glual Innova.

Objetivos y resultados

El objetivo principal de MAINWIND+ fue prolongar la vida útil y la rentabilidad de los parques actuales mediante la incorporación de componentes inteligentes y plataformas en la nube para soluciones globales en operación y mantenimiento predictivo (ver Figura 12). En concreto Tekniker participó en los siguientes resultados:

- Definición de una nueva metodología de análisis de riesgo on-line que tenga en cuenta los factores dinámicos para su cálculo, de forma que posteriormente pueda ser utilizado en las actividades de mantenimiento a realizar en los aerogeneradores.

- Un algoritmo de optimización conjunta para la logística y el mantenimiento, que proporcione las cantidades de stock en el almacén a la vez que se ajustan las frecuencias de inspección en el plan de mantenimiento.

- Un algoritmo para la estandarización de la definición de planes de mantenimiento y a su vez la optimización de la planificación del mantenimiento del parque.

Figura 12. Diagrama conceptual del Proyecto MAINWIND+

1.8 Listado de publicaciones

Esta memoria de tesis está principalmente basada en las contribuciones publicadas en revistas y conferencias recopiladas en este capítulo. Dichas publicaciones incluyen contribuciones a las áreas de E-mantenimiento e interoperabilidad, Diagnóstico de fallos, Simulación de estrategias y Optimización de la planificación. A continuación, se detalla la lista completa de artículos del autor, remarcando en negrita los incluidos en esta memoria.

Revistas JCR

- *Gilabert, E., & Arnaiz, A. (2006). Intelligent automation systems for predictive maintenance: A case study. Robotics and Computer-Integrated Manufacturing, 22(5-6), 543-549. JCR Q2.*

- ***Gilabert, E., Fernandez, S., Arnaiz, A., & Konde, E. (2015). Simulation of predictive maintenance strategies for cost-effectiveness analysis. Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture, 231(13), 2242-2250. JCR Q3.***

- ***Gilabert E., Konde E., Arnaiz A., Sierra B. (2020). A multi-objective hybrid EDA-based algorithm for optimizing preventive maintenance plans. Reliability Engineering & System Safety. Submitted in Revision process. JCR Q1.***

Otras revistas y capítulos de libros

- *Gilabert, E., & Arnaiz, A. (2005). Uso de Sistemas Expertos Probabilísticos para aplicaciones de mantenimiento y diagnóstico: Una tecnología para tratar la incertidumbre y la adaptación. Mantenimiento: ingeniería industrial y de edificios, (187), 39-46.*

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1.9 Estructura de este documento

Esta memoria de tesis está dividida en 8 capítulos principales, incluyendo este capítulo introductorio.

Capítulo 2

Esta sección pone en relevancia las tecnologías para dar soporte a las estrategias relacionadas con el mantenimiento predictivo en continuo (*on-line*), en especial los sistemas inteligentes de ayuda en la monitorización, diagnóstico y toma de decisiones. Presenta dos contribuciones: una plataforma capaz de proporcionar servicios web de mantenimiento avanzado, llamada DYNAWeb; un modelo de datos para la gestión y el mantenimiento de la configuración, teniendo en cuenta todo el ciclo de vida de los activos.

Capítulo 3

Este capítulo propone el uso de las Redes Bayesianas junto con otras metodologías de recogida de información utilizadas en ingeniería para automatizar la tarea de diagnóstico y predicción de fallos. Presenta dos contribuciones: el desarrollo de una Red Bayesiana de diagnóstico para máquina herramienta basándose en la información del espectro de vibraciones; una metodología que automatiza la generación de modelos de diagnóstico con incertidumbre y aprendizaje, mediante la combinación de las características y propiedades de un Análisis de Modos de Fallos y Efectos (AMFE) y de las Redes Bayesianas.

Capítulo 4

El objetivo principal de este capítulo es centrarse en tecnologías que permitan optimizar las estrategias de mantenimiento, ya sea con diseños más fiables o mediante la mejora en las decisiones de mantenimiento. Presenta dos contribuciones: una metodología para la selección de la mejor estrategia coste-efectiva de mantenimiento, que emplea una simulación partiendo de la distribución de densidad de probabilidad de fallo para el equipo o componente mediante la utilización de históricos de fallos; un nuevo algoritmo de optimización multiobjetivo para resolver el problema de optimización combinatoria en la definición de los planes de mantenimiento.

Capítulo 5

En esta sección presenta un resumen de las principales contribuciones de este proyecto de tesis. La mayoría de estas contribuciones han sido presentadas en revistas y conferencias.

Capítulo 6

Este capítulo describe las principales conclusiones de este proyecto de tesis y ofrece una visión de futuro en la aplicación de tecnologías de Inteligencia Artificial para la mejora de las estrategias y procesos de mantenimiento.

Capítulo 7

El capítulo 7 contiene las referencias bibliográficas empleadas para la redacción de esta memoria de tesis.

Capítulo 8

Las principales publicaciones que apoyan el trabajo de investigación se presentan en este último capítulo. Dichas publicaciones incluyen contribuciones a las áreas de: e-mantenimiento e interoperabilidad; diagnóstico de fallos; simulación de estrategias y Optimización de la planificación.

2 E-mantenimiento e Interoperabilidad

Esta sección tiene especial relevancia para dar soporte a las estrategias relacionadas con el mantenimiento predictivo en continuo (on-line) de forma que puedan utilizarse las últimas tecnologías del mercado, y en especial los sistemas inteligentes de ayuda en la monitorización, diagnóstico y toma de decisiones. Su continua reducción de costes ofrece claras oportunidades de mejora en los procesos de mantenimiento. Las tecnologías predictivas han evolucionado en estos últimos años y se están realizando avances importantes en aplicaciones mecánicas, térmicas, electromecánicas y más actualmente en sistemas eléctricos y electrónicos.

El e-mantenimiento está relacionado con el desarrollo de plataformas colaborativas e inteligentes que permiten la integración de nuevos sensores, sistemas de comunicaciones, estándares y protocolos, conceptos, métodos de almacenamiento y análisis etc. que entran continuamente en nuestro abanico de opciones y nos ofrecen la posibilidad de seguir una tendencia de mejora en la optimización de activos y procesos, y en la interoperabilidad entre sistemas. También está relacionado con dar facilidades y soporte a la interoperabilidad y conectividad de nuevos sistemas.

2.1 Antecedentes

El e-mantenimiento aparece como un cambio en los objetivos del mantenimiento una vez que está claro que es un actor de primer orden para conseguir unos niveles mayores de sostenibilidad social y medioambiental, en donde es necesario tener en cuenta el ciclo de vida completo de los activos para evaluar correctamente el valor real de cada producto y cada proceso [Takata et al., 2004]. También es de gran importancia en contextos en donde un fallo puede conducir a un mal producto o servicio, pudiendo impactar de forma importante en el negocio dependiendo de la función que se deja de cumplir a causa del fallo.

En ambos contextos es necesario el paso a estrategias dinámicas, que permitan moverse desde estrategias correctivas (*fail & fix*) a predictivas '*predict & prevent*' [Lee et al., 2006] incluyendo el mantenimiento integrado en los procesos de una empresa. El mantenimiento basado en condición (*Condititon Based Maintenance* – CBM) es una de las prácticas que ilustra mejor este cambio. Pero para que este tipo de mantenimiento sea factible dentro de los procesos de la empresa es necesario:

a) Analizar y decidir sobre un conjunto de datos e información cada vez más amplio y heterogéneo, que se va ampliando a medida que la sensorización, comunicación y almacenamiento de estos se hace más eficiente.

b) Integrar las decisiones y procesos con el resto de la información de la empresa.

Sin embargo, este cambio en el concepto de mantenimiento se ve comprometido por la falta de sistemas de mantenimiento flexibles y rentables. Este desafío está particularmente relacionado con la poca relevancia que las estrategias avanzadas de mantenimiento han alcanzado hasta ahora, como el CBM y el mantenimiento predictivo (*Predictive Maintenance* – PdM). Según [Komonen, 2005], alrededor del 30% de todas las actividades de mantenimiento en sistemas industriales y de transporte en Europa no están planificadas, mientras que un 55% de las actividades están relacionadas con el mantenimiento planificado y programado. Es decir, el 85% de las estrategias de mantenimiento implica costes de acción innecesarios y averías de maquinaria o acciones de servicio como el desmontaje que tienen efectos negativos en el rendimiento y la vida útil de los componentes. Una razón importante para esta falta de aplicación puede estar en la necesidad de información.

Incluir y mantener un sistema basado en el conocimiento, capaz de ayudar a los técnicos a determinar las mejores soluciones, no es una tarea fácil. El conocimiento en el área todavía está disperso, con mucha información existente para técnicas bien conocidas (por ejemplo, vibraciones, motores eléctricos), pero más escasa en otras técnicas menos establecidas (por ejemplo, emisión acústica, máquinas herramientas). Además, es necesario adaptar la información a medida que se deben controlar las nuevas condiciones de operación, el conocimiento en muchos campos crece anualmente, y finalmente mientras aparecen nuevos dispositivos (por ejemplo, sensores) que proporcionan nueva información [Arnaiz et al., 2004].

Por otro lado, la Web Semántica es un proyecto que pretende crear un medio universal para el intercambio de información dando significado (semántica) de forma comprensible por las máquinas, al contenido de los documentos en la web [Berners-Lee et al., 2001]. La Web Semántica (*Semantic web* – SW) ofrece muchas ventajas que hacen que las aplicaciones web sean más útiles e independientes del ser humano, pero también, su uso podría aumentar las ganancias de las empresas ya que las técnicas de SW mejoran la eficiencia de estas aplicaciones. Las principales ventajas [Carro-Martínez, 2005] son mejorar en general las búsquedas en la web, favorece la integración entre distintos componentes, la estandarización, y la composición de sistemas complejos.

Para hacer frente a estos desafíos el trabajo que se presenta en esta sección se enfoca en 2 líneas de contribución para facilitar la interoperabilidad e inclusión de datos y servicios inteligentes: la primera tiene que ver con el diseño y desarrollo de una plataforma flexible basada en estándares abiertos, y en concreto en OSA-CBM *(Open System Architecture for Condition Based Maintenance)*, que permita la integración de diferentes módulos que pueden convertirse en servicios web, incluyendo además tecnologías semánticas para facilitar esta interoperabilidad; la segunda contribución realiza una revisión de los estándares de interoperabilidad existentes para gestión del mantenimiento, más allá del estándar OSA-CBM, buscando su integración con los procesos de gestión de configuración de un activo.

2.2 Contribuciones

A continuación, se describen las dos contribuciones con relación a este capítulo sobre e-mantenimiento e interoperabilidad: una plataforma capaz de proporcionar servicios web de mantenimiento avanzado, llamada DYNAWeb; un modelo de datos para la gestión y el mantenimiento de la configuración, teniendo en cuenta todo el ciclo de vida de los activos.

2.2.1 Servicios web Inteligentes en e-mantenimiento

Los servicios web son una tecnología bien conocida que se utiliza en entornos industriales. Ofrecen interoperabilidad entre aplicaciones de software independientes a través de Internet mediante el protocolo SOAP (*Simple Object Access Protocol*) que permite la comunicación. El trabajo realizado en esta sección está relacionado con el desarrollo de una plataforma capaz de proporcionar servicios web de mantenimiento avanzado, llamada DYNAWeb.

DYNAWeb es una plataforma de información y comunicación que proporciona interacción operativa entre tecnologías *plug-in* en el marco de un escenario de información distribuida, donde las tecnologías de interés pueden variar de un caso de uso de mantenimiento a otro [Jantunen et al., 2008]. Para desarrollar esta plataforma, se realizó un estudio de posibles actores asociados a futuras actividades de DYNAWeb. La síntesis aparece en la Tabla 1, que identifica: el papel principal identificado en cada caso; los datos esperados; y su participación esperada en los pasos de procesamiento de información en capas de OSA-CBM.

Tabla 1. Principales funciones de los actores en DYNAWeb

Actor	***Función***	***Tipo de datos***	***Niveles OSA-CBM***
Experto de mantenimiento	Decisiones estratégicas sobre mantenimiento de acuerdo con la política empresarial	Políticas	
GMAO / ERP	Gestión del ciclo de vida de las órdenes de trabajo de mantenimiento, de acuerdo con la estrategia de mantenimiento seleccionada	Información de repuestos, órdenes de trabajo, fallos, indicadores	Operacional Soporte a decisiones
Sistema informatizado mantenimiento operacional (CMOpS)	Apoyo en los procesos dinámicos de mantenimiento para seleccionar la mejor orden de trabajo de mantenimiento y ejecutarla	Datos históricos/tendencias Datos de fiabilidad	Predicción Diagnóstico
Dispositivo móvil	Ayudar al técnico de mantenimiento a realizar las tareas cotidianas. Para incluir funcionalidad del CMOpS	Datos operacionales	Monitorización de estado Procesado de señal
Sensores	Generar datos e información sobre el estado de la máquina	Datos de estado	Monitorización de estado Procesado de señal Adquisición de datos
Etiquetas inteligentes	Automatizar la identificación de máquina/pieza y entregar información histórica sobre el estado de la máquina	Datos identificativos	Procesado de señal

Una vez que se identificaron los actores, estos se han enmarcado en una arquitectura flexible con respecto a los canales de comunicación entre los actores. La Figura 13 proporciona una visión general esquemática del concepto de sistema completo representado para las tecnologías de información y comunicación que se consideran dentro de la plataforma DYNAWeb. Esta vista identifica la existencia de tres capas con la ubicación de los actores con respecto a la empresa, y también indica la interoperabilidad de estos actores con diferentes tecnologías.

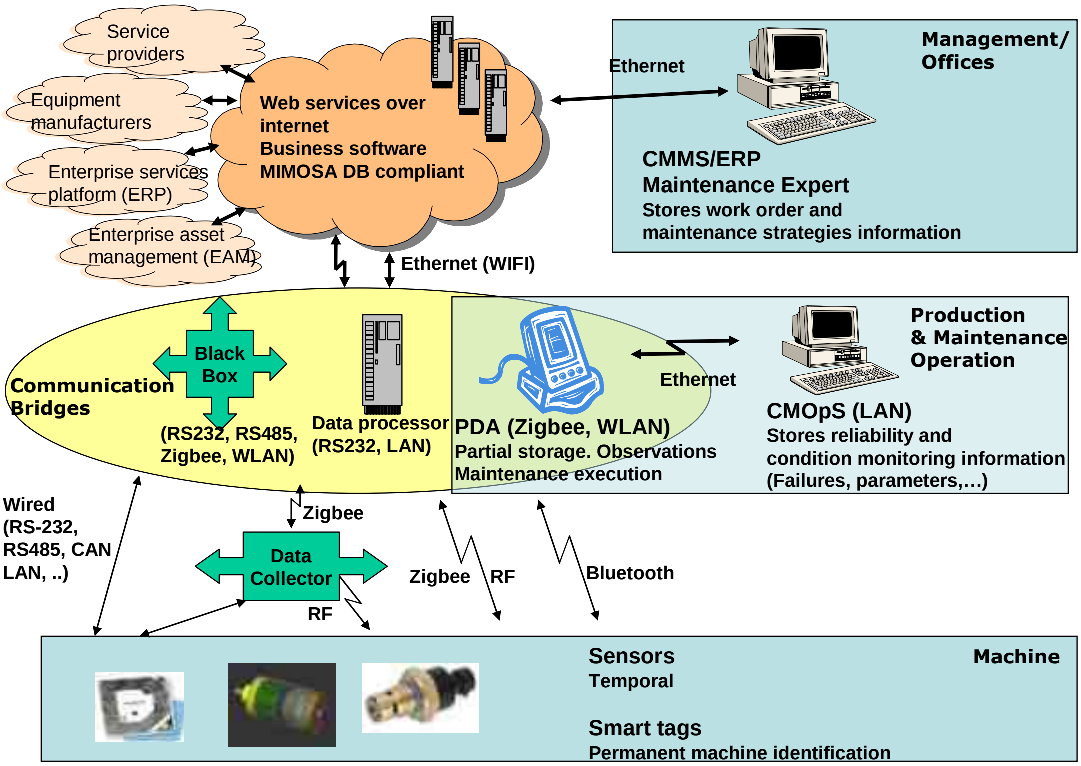

Figura 13. Arquitectura de plataforma DYNAWeb

El primer nivel corresponde a la máquina e identifica sensores y etiquetas inteligentes asociadas a este nivel de interoperación. También se espera que los sensores contengan información temporal sobre los valores de la condición actual, con poca o ninguna información histórica adjunta. El segundo nivel corresponde al taller de producción e identifica dos actores principales: el asistente digital personal (*Personal Digital Assistant* – PDA) y el Sistema informatizado mantenimiento operacional (Condition Maintenance Operational System – CMOpS). Las PDA pueden contener información temporal sobre las actividades del operador y los valores de entrada, y el CMOpS mantendrá registros históricos sobre la información de la condición seleccionada. El tercer nivel corresponde a la sede y al personal de gestión, donde se toman decisiones tácticas y estratégicas. El sistema GMAO (Gestión del Mantenimiento Asistido por Ordenador) y los agentes expertos en mantenimiento se encuentran en este nivel, junto con información sobre las operaciones programadas y las estrategias de mantenimiento.

La posibilidad de integrar servicios independientes entre sí que puedan interoperar es un aspecto central de la plataforma DYNAWeb. Para proporcionar el flujo de análisis más conveniente, el procesamiento de información se entiende como un sistema distribuido y colaborativo, donde hay diferentes niveles de entidades que pueden realizar tareas de inteligencia. Dado esto, con la ayuda de los Diagramas de casos de uso (*Use Case Diagram* – UCD) que utilizan el lenguaje de modelado unificado (*Unified Modeling Language* – UML) estándar, se ha definido una arquitectura de sistema para identificar las interacciones entre los actores y las funciones requeridas. De particular importancia es la definición UCD para Operación, Evaluación y ejecución de Tareas (ver Figura 14). La especificación de este UCD incluye 4 capas que corresponden a las capas centrales de procesamiento de información del estándar OSA-CBM [Lebold et al., 2002][Bengtsson, 2003]:

- Monitorización de estado: recibe datos de los módulos de sensor y los módulos de procesamiento de señal. Su enfoque principal es comparar los datos con los valores esperados. Esta capa debe ser capaz de generar alertas basadas en límites operativos preestablecidos o cambios en la tendencia.

- Evaluación de salud: recibe datos de diferentes fuentes de monitoreo de condición o de módulos de evaluación de salud. El enfoque principal del módulo de evaluación de salud es prescribir si la salud del componente, subsistema o sistema monitoreado se ha degradado, además de generar registros de diagnóstico y proponer posibilidades de fallo. El diagnóstico se basa en las tendencias en el historial de salud, el estado operativo y el historial de carga y mantenimiento.

- Pronósticos: este módulo tiene en cuenta los datos de todas las capas anteriores. El objetivo principal del módulo de pronóstico es calcular el estado futuro de un activo, teniendo en cuenta los perfiles de uso futuros. El módulo informa el estado de fallo de un tiempo específico o la vida útil restante (*Remaining Useful Life* – RUL).

- Soporte de decisiones: en este contexto, está relacionado con "Programar órdenes de trabajo". El GMAO programa las órdenes de trabajo según las predicciones de los componentes. Después de eso, distribuye órdenes de trabajo a diferentes operadores a través de su dispositivo móvil. Los dispositivos móviles necesitan leer las etiquetas inteligentes para aprender sobre los componentes [Adgar et al., 2007].

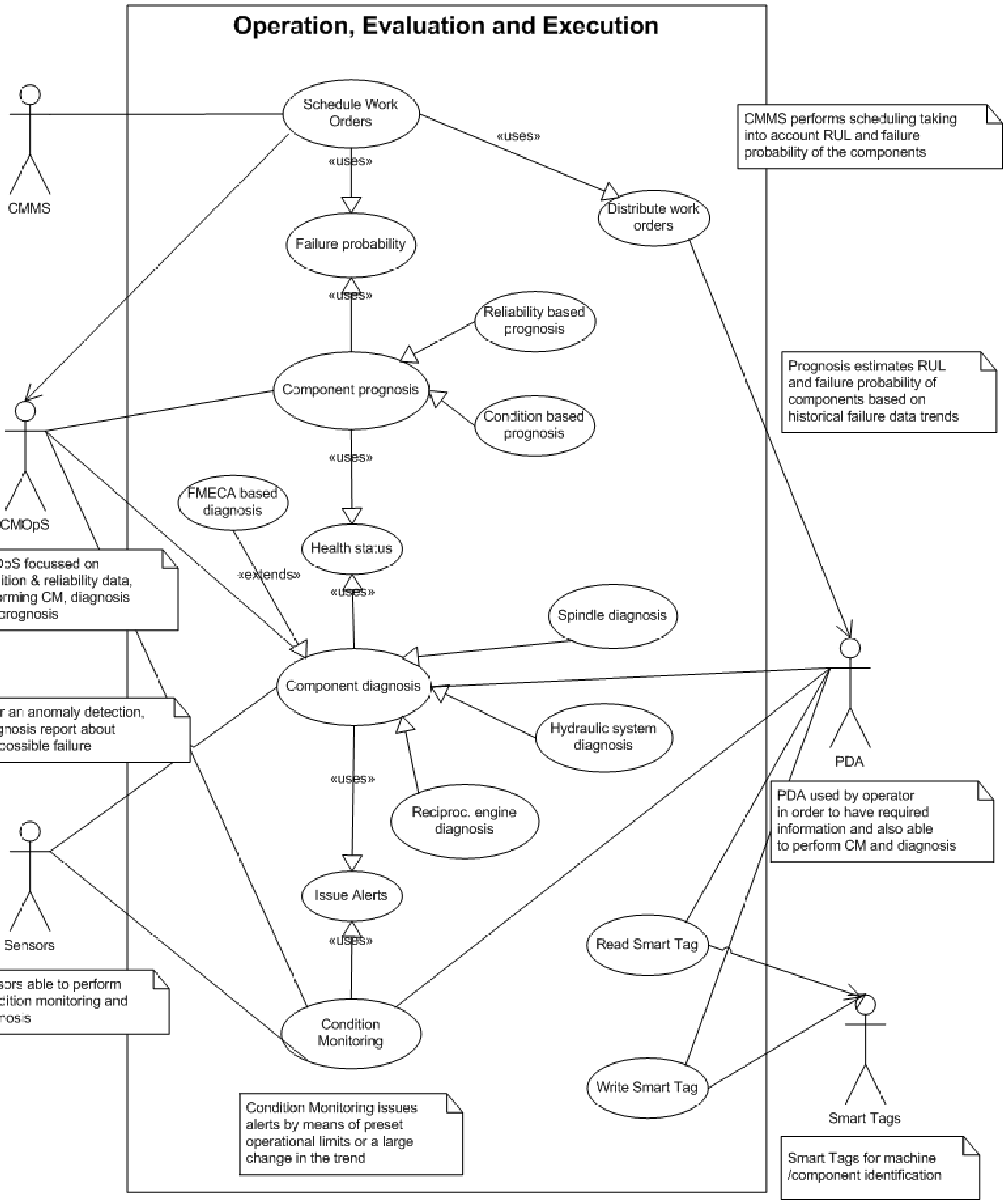

Figura 14. Diagrama de casos de uso para operación, evaluación y ejecución.

Uno de los desafíos es hacer coincidir el concepto de web semántica con la función de mantenimiento. De esta manera, la información utilizada en Internet debe especificarse en ontologías. La ontología representa el conocimiento en Internet [Fensel, 2001], definiendo de manera formal los conceptos de los diferentes dominios y relaciones, con capacidad de razonar sobre este conocimiento. En este caso, la definición de ontologías se realizó a partir de MIMOSA CRIS (*Common Relational Information Schema*). CRIS representa una vista estática de los datos producidos por un sistema CBM, donde cada capa OSA-CBM se ha asociado a la ontología [Lebold et al., 2002].

OSA-CBM se desarrolló alrededor de MIMOSA CRIS que brinda cobertura de la información (datos) que se administrará dentro de un sistema de mantenimiento basado en la condición. Define un esquema de base de datos relacional con aproximadamente 400 tablas para información de mantenimiento de maquinaria. En resumen, CRIS es el núcleo de MIMOSA que tiene como objetivo el desarrollo y la publicación de convenciones abiertas para el intercambio de información entre sistemas de información de mantenimiento de planta y maquinaria, y los servicios web de DYNAMITE se crean utilizando el estándar CRIS para interoperabilidad e información interna. Procesando.

Otro gran desafío fue abordar este concepto para los recursos informáticos cotidianos, así como para los servicios móviles. En este sentido, con respecto al uso de estos servicios web, hay tres elementos principales definidos que participan en la comunicación:

- El actor de Interfaces hombre-máquina (*Human Machine Interface* – HMI), es decir, una interfaz de software para el técnico en el escritorio o con el dispositivo móvil, e interactuando con sistemas de bases de datos locales o centrales que solicitan a los servicios web que procesen información específica.

- Agente para comunicarse con los servicios web de DYNAWeb. El agente puede obtener los datos necesarios de otras fuentes, traduciéndolos al lenguaje de ontología. De esta forma, el agente actúa como una interfaz entre HMI y el servicio web.

- Servicio web, que realiza el servicio solicitado, soportado por ontologías.

Con esta configuración en mente, se ha desarrollado una arquitectura flexible de interacción de datos para proporcionar el mejor acceso dependiendo de los agentes y repositorios de datos disponibles. Esto significa que, una vez que el técnico ha solicitado un resultado específico, el agente puede utilizar principalmente dos opciones de comunicación diferentes, como se muestra en la Figura 15.

- La comunicación directa con la base de datos se puede realizar si la base de datos cumple con la especificación MIMOSA. Luego, el agente solo transmite comandos XML (*eXtensible Markup Language*) al servicio web, que a su vez accede a la base de datos para los datos.

- Si la base de datos local no es compatible con MIMOSA, el agente puede optar por enviar los datos en formato XML.

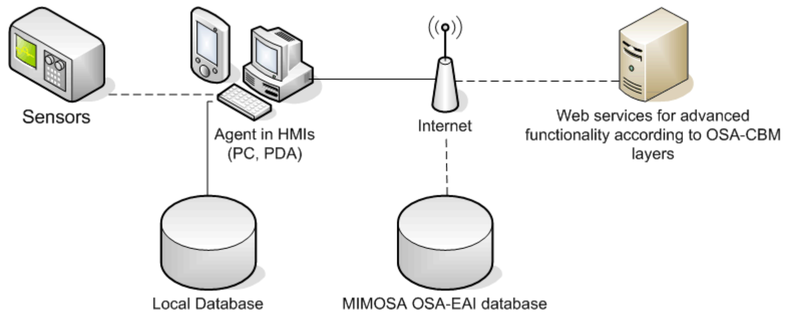

Figura 15. Arquitectura de comunicación entre HMI y servicios web, mediante el uso de un agente que almacena datos en la base de datos MIMOSA

Como ejemplo de esta interacción, la Figura 16 muestra un diagrama de secuencia para solicitar un servicio de diagnóstico, con comunicación directa enviando datos en formato XML. La ejecución de cada función de diagnóstico sigue los siguientes pasos:

1. Aceptación y validación del archivo XML.
2. Extracción de datos del archivo XML.
3. Generación de alertas de diagnóstico con probabilidades y severidades asociadas. Dependiendo del componente, el servicio puede administrar uno o más objetos para emitir una evaluación de salud:
   a. Una Red Bayesiana.
   b. Un sistema experto CLIPS (*C Language Integrated Production System*) basado en reglas.
   c. Definición AMFE (Análisis de modos de fallos y efectos).
4. Analizar alertas al archivo XML.
5. Devolver el archivo XML al agente.

6. Es necesario realizar una inspección visual u otra prueba, el agente podría solicitar en un segundo paso el servicio de diagnóstico con información adicional.

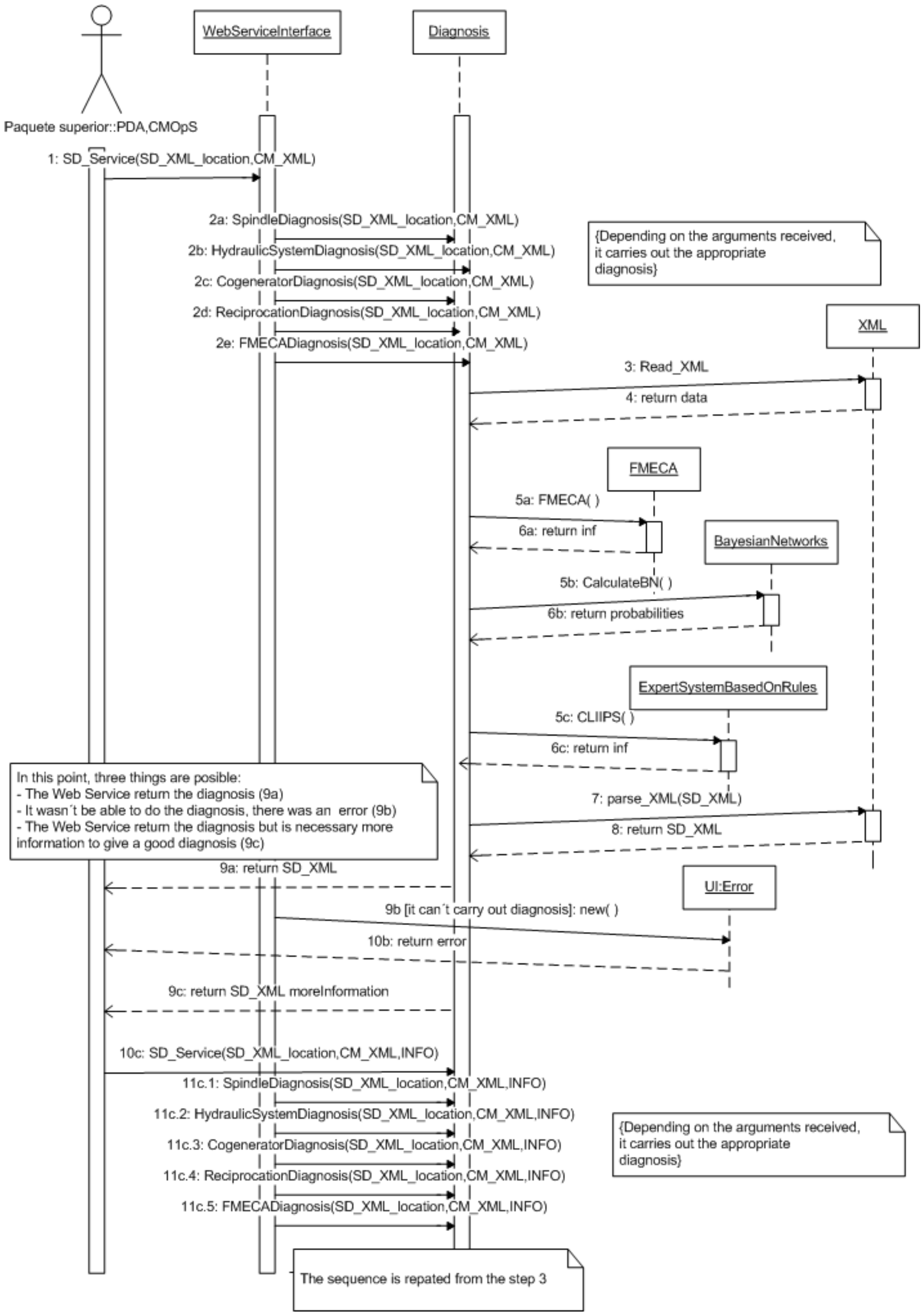

Figura 16. Diagrama de secuencia para el servicio web de diagnóstico

En este ejemplo, es interesante señalar cómo los actores PDA y CMOpS comparten el mismo acceso a los servicios web. Pr último, este ejemplo muestra que es posible enmarcar los sistemas de procesos existentes dentro de los servicios web con formato CRIS, para aprovechar la inteligencia ya existente. Por ejemplo, uno de los procesos de diagnóstico existentes se basa en sistemas previamente desarrollados [Gilabert & Arnaiz, 2006] que utilizan Redes Bayesianas para facilitar un modelo que pueda funcionar con incertidumbre y que también pueda adaptarse con información de retroalimentación. En este sentido, la mayoría de los servicios web se han desarrollado utilizando la plataforma Microsoft .NET como una aplicación web, utilizando el entorno de programación Microsoft Visual Studio .NET y la base de datos implementada con el servidor Microsoft SQL Server.

El objetivo final de este desarrollo es facilitar el acceso de cada empresa a los grandes cambios y oportunidades que se producen en el mantenimiento actual. Se espera que el potencial de este enfoque de e-mantenimiento realmente brinde oportunidades para obtener beneficios económicos para toda la gama de empresas.

2.2.2 Modelo de datos para e-mantenimiento e interoperabilidad

La interoperabilidad entre las diferentes tecnologías que componen un sistema de mantenimiento basado en condición (como por ejemplo sensórica y adquisición de datos, manipulación/preprocesado, sistemas de diagnóstico y pronóstico, interfaces en sistemas desktop y móviles, etc.) requiere de un esfuerzo considerable. Aunque la contribución explicada en la sección anterior se ha basado en el soporte del estándar OSA-CBM[3], y su derivada en la norma ISO-13374 [ISO 2012], esta no abarca otros aspectos importantes de la gestión del mantenimiento, como es la gestión de la configuración de un activo.

El objetivo de este segundo trabajo de investigación ha sido el definir un modelo de datos para la **gestión y el mantenimiento de la configuración**, teniendo en cuenta todo el ciclo de vida de los activos. La gestión de la configuración (*Configuration management* – CM) es el proceso para identificar las características físicas y funcionales de un elemento de configuración (*Configuration item* – CI) durante todo el ciclo de vida (software, firmware o

[3] https://www.mimosa.org/mimosa-osa-cbm/

hardware), controlar todos los cambios en características, registrar y procesar los informes de cambios y controlar el estado de implementación.

El propósito central de CM es permitir una mejor toma de decisiones, en productos, proyectos y programas, para controlar los cambios a través de la creación y mantenimiento de documentación y productos con la capacidad de hacer referencia a estos datos en cualquier momento. En este contexto, la gestión de la configuración conduce a un mantenimiento más efectivo. Por ejemplo, es posible tener una mejor trazabilidad del equipo, teniendo en cuenta todos los cambios que tiene el equipo, mejorar la logística de mantenimiento conociendo la configuración real de un activo, o comparar entre la configuración de dos máquinas para seleccionar la mejor para la empresa.

Tabla 2. Estándares relacionados con mantenimiento y CM

Estándar	***Descripción***	***Modelo de datos***
ISO 10303	Estándar de datos para un modelo de producto.	Guías para datos de productos, geometría, información relacionada con piezas
GEIA 927	Esquema de datos común para sistemas complejos.	Guías para la arquitectura del producto, del sistema físico y funcional durante el ciclo de vida.
ANSI/EIA 836	Intercambio de datos para la gestión de la configuración.	Esquemas XML que admiten CM
ANSI/EIA 649	Gestión de la configuración de forma general.	Guías para la gestión de la configuración.
MIMOSA OSA-EAI	Arquitectura para las actividades de Operación y Mantenimiento	Esquemas XML y una base de datos para soportar mantenimiento, monitoreo de condiciones, operación y fiabilidad
ASD/AIA S1000D	Especificaciones para publicaciones técnicas.	Esquemas XML y una base de datos que admite tipos de información como descriptivos, de procedimientos, programas de mantenimiento, aislamiento de fallos y tripulación / operadores
PAS 55	Norma británica para la gestión de activos	Guías para la gestión de recursos, análisis de coste-beneficio, riesgos y ciclo de vida.
IEC 60300	Gestión de la fiabilidad y costeo del ciclo de vida	Guías para la fiabilidad y el coste del ciclo de vida

El CM está respaldado principalmente por el modelo de datos empleado. Existen varios estándares para la gestión de la configuración o la ejecución del mantenimiento, pero no se ha llevado a cabo ningún trabajo previo para intentar integrar un modelo de datos de gestión de la configuración en el campo del mantenimiento. Por esta razón, hemos considerado la necesidad de definir un modelo de datos de manera amplia, teniendo en cuenta aspectos relacionados con la ejecución del mantenimiento, la logística, los costes, el estado y la fiabilidad, así como la identificación y el control de la configuración.

El primer paso fue revisar los sistemas relacionados con la gestión de la configuración, comprobar la utilización de estándares y normas que están conectados de manera práctica y buscar la relación de los diferentes modelos de datos posibles utilizados para los sistemas de gestión de la configuración. La Tabla 2 resume las normas más importantes [Pratt, 2001][Rachuri, 2008][Bsi, 2008][Colson, 2006][EIA, 2010][EIA, 2011][IEC, 2004][Mathew, 2010].

Seguidamente, se ha trabajado en realizar una definición de modelo de datos que aglutine toda la información necesaria, que ha dado como resultado una organización en 7 capas de información, de acuerdo con los diferentes puntos de vista de un activo:

- Identificación de la configuración: identificación física o funcional del hardware o software en todo el ciclo de vida.
- Histórico de rediseños: registro de modificación de la configuración de activos.
- Localización: información relacionada con la ubicación del activo.
- Ejecución y logística del mantenimiento: secuencia de pasos para completar una tarea de mantenimiento, herramientas, materiales, personal para completar las tareas de mantenimiento, ubicación y política de mantenimiento (información de política correctiva, preventiva y predictiva)
- Costes: información relacionada con los costes de mantenimiento, reparación y repuestos.
- Condición: estado de salud de los activos, predicción de salud, detección, mediciones e inspecciones.
- Fiabilidad: datos históricos de tareas de mantenimiento completadas, datos de fiabilidad de diseño y fallos.

Estas 7 capas presentan información muy diversa, que es difícil de abarcar con un solo estándar, por lo que se ha realizado un análisis de todos ellos para identificar cuales pueden dar soporte a cada capa de información. El resultado se presenta en la Tabla 3.

Tabla 3. Capas de información y estándares relacionados

CAPA DE INFORMACIÓN	NORMAS/ ESTÁNDARES
IDENTIFICACIÓN DE LA CONFIGURACIÓN	ISO 10303 GEIA-927 EIA-836 EIA-649 OSA-EAI
HISTÓRICO DE REDISEÑOS	ISO 10303 GEIA-927 EIA-836 EIA-649
LOCALIZACIÓN	MIMOSA OSA-EAI
EJECUCIÓN Y LOGÍSTICA	ASD/AIA-S1000D MIMOSA OSA-EAI PAS 55 IEC 60300
CONDICIÓN	ASD/AIA-S1000D MIMOSA OSA-EAI
COSTES	PAS 55 IEC 60300
FIABILIDAD	MIMOSA OSA-EAI PAS 55 IEC 60300

MIMOSA OSA-EAI (*Open System Architecture for Enterprise Application Integration*) se asigna en la mayoría de las capas de datos, lo que lo convierte en el estándar más adecuado desde una perspectiva amplia. En este sentido, podría ser coherente seleccionar OSA-EAI como nuestro estándar para la gestión de la configuración y el modelo de datos de mantenimiento, pero esta selección tiene varios inconvenientes. Primero, se centra más en la comunicación entre diferentes aplicaciones que en la integración de diferentes tipos de datos en un modelo de datos único. Por esta razón, esta base de datos está compuesta por cientos de tablas, lo que dificulta su uso y su actualización. Además, OSA-EAI no admite ni la gestión de la configuración ni los costes durante el ciclo de vida.

Teniendo en cuenta eso, OSA-EAI puede usarse como punto de partida en nuestro modelo de datos, pero necesita una simplificación para ser más operativo y una integración de otros estándares que cubran sus brechas. Por lo tanto, nuestro modelo de datos está compuesto por la conjunción de 3 estándares:

- MIMOSA OSA-EAI: estándar seleccionado para identificación de configuración, localización de activos, ejecución del mantenimiento, logística y política, condición y fiabilidad.

- EIA-836: estándar seleccionado para registrar los cambios de activos. Este estándar también proporciona una definición de base de datos, lo que facilita su integración con OSA-EAI.

- IEC 60300: estándar que proporciona un modelo de coste basado en el coste del ciclo de vida

Finalmente, se ha aplicado este nuevo modelo en un caso de uso donde se verifican los problemas del modelo de datos con el fin de mejorarlo. El objetivo principal era tener un manejo y tratamiento de la información más fácil, en lugar de tener un modelo "perfecto". Con una visión práctica de las pruebas el modelo de datos se ha ajustado, a fin de obtener un nuevo modelo conceptual, más ágil para los futuros usuarios y como consecuencia, menos difícil de mantener.

Por un lado, las capas de ejecución del mantenimiento, políticas y logística se han integrado en una capa única debido a la relativa simplicidad de las capas de logística y políticas. Por otro lado, se han eliminado varias definiciones de objetos de nuestro modelo de datos para no aportar ninguna información relevante, y otras se han agrupado o convertido a otros parámetros asociados a objetos. En la Tabla 4 se detallan los cambios realizados en las nuevas 7 capas.

Finalmente, se define un modelo de datos conceptual que se resumen en la Tabla 5, indicando los objetos principales propuestos en cada capa.

Tabla 4. Cambios realizados en el modelo de datos

CAPA DE INFORMACIÓN	CAMBIOS REALIZADOS
IDENTIFICACIÓN DE LA CONFIGURACIÓN	Eliminación de la clase *BaseDeDatos* en OSA-EAI
HISTÓRICO DE REDISEÑOS	Simplificación de estructura de EIA-836B: Conversión de clase a propiedades: *Fecha, AutorizadoPor, Descripcion, DescripciónModificacion, PruebasRealizadas.*
LOCALIZACIÓN	Estándar OSA-EAI: modificaciones en la definición de la clase de posición *Mapa* y simplificación de la definición de GPS
EJECUCIÓN Y LOGÍSTICA	OSA-EAI distingue entre eventos de Activos y Segmentos. Simplificación de la estructura, sin la duplicidad. Eliminación de clase *Auditoria.*
COSTES	Sin restricciones
CONDICIÓN	Estructura de condición en OSA-EAI asignada al segmento. Modificaciones en la estructura, más flexible para Activos y Segmentos.
FIABILIDAD	OSA-EAI tiene duplicidad en la estructura de Activos y Segmentos. Simplifación de la estructura y eliminación de clases.

Cuando comparamos el modelo de datos propuesto con el disponible en un software GMAO (Gestión del Mantenimiento Asistido por Ordenador) tradicional, podemos definir las siguientes ventajas:

- Gestión eficiente de la configuración, sin duplicidades.
- Trazabilidad de cambios realizados sobre el activo.
- Activos que cambian de activo padre (desmontajes).
- Localización de activo fuera de su ubicación habitual.
- Asociación de configuración a órdenes de trabajo.
- Costes del Activo en todo el ciclo de vida.
- Costes a nivel de operaciones de mantenimiento.
- Gestionar el preventivo asociado a la posición o el elemento físico.

- Establecimiento de parámetros con los que realizar el mantenimiento preventivo.

- Gestión de configuración junto con fiabilidad, teniendo en cuenta el histórico de cambios realizados.

Tabla 5. Resumen del modelo de datos final

CAPA DE INFORMACIÓN	DESCRIPCIÓN	OBJETOS PRINCIPALES
IDENTIFICACIÓN DE LA CONFIGURACIÓN	Identificación física o funcional del hardware o software en todo el ciclo de vida.	Empresa, Emplazamiento, Activo, Segmento, Tipo_Activo, Tipo_Segmento, Agente, Fabricante, Modelo
HISTÓRICO DE REDISEÑOS	Registro de modificaciones de la configuración del activo.	Activo, Segmento, Modificacion_realizada, Agente, Mod_añadido, Mod_borrado, Mod_editado, Mod_reemplazado
LOCALIZACIÓN	Información relacionada con la ubicación del activo.	Activo, Segmento, Agente, Posición, Dirección, GPS, Activo_Position, Segmento_Position, Agente_Position
EJECUCIÓN Y LOGÍSTICA	Secuencia de pasos para realizar una tarea de mantenimiento, herramientas, materiales y personas necesarias para realizar el mantenimiento y su ubicación.	Activo, Segmento, Evento, Recomendación, Solicitud_trabajo, Orden_trabajo, Operación, Defecto, Herramienta, Emplazamiento, Documentación, Agente, Subcontratación, Orden_completada, Causa, Acción
COSTES	Costes de mantenimiento, reparación y repuestos. Estrategias de mantenimiento aplicadas a la información de activos, correctivos, preventivos, predictivos y otros.	Activo, Segmento, CosteDiseñoFabricacion, CosteDistribución, CosteOperación, CosteMantenimiento, CosteFindeVida, CosteAlmacenamiento, CosteRiesgo, CosteTareaMantenimiento
CONDICIÓN	Estado de salud de los activos, predicción de salud, detección, mediciones e inspecciones.	Emplazamiento, Medidor, Medida, Unidad, Activo, Segmento, Alarma_Region, Tipo_Alarma, Evento, Recomendación, Agente
FIABILIDAD	Datos históricos de tareas de mantenimiento completadas, datos de fiabilidad de diseño y fallos.	Activo, Segmento, Modelo, Función, Funcion_Evento, Funcion_Recomendacion, Eevento, TipoEvento, Medición, Agente, Recomendación

La definición de este modelo de datos permitirá un mantenimiento más efectivo a través de una mejor trazabilidad del equipo, también mejorará la logística de mantenimiento, conocerá la configuración real de un activo o permitirá realizar comparaciones entre la configuración de varias máquinas. Los siguientes pasos continuarán trabajando en el modelo de datos conceptual en relación con la adquisición de datos en línea con el modelo.

2.3 Conclusiones y trabajo futuro

La contribución más novedosa que se incluye en este capítulo es la definición de un marco de desarrollo semántico, basado en la arquitectura OSA-CBM y la sincronización del interfaz CRIS con una ontología (definida a nivel de XML/UML), para facilitar la interoperabilidad entre servicios web diseñados de forma independiente y que interactúan en un entorno distribuido con diferentes actores y sistemas, cada uno con una función a desempeñar. La segunda contribución va más allá del estándar OSA-CBM, realizando una revisión de los estándares de interoperabilidad existentes para gestión del mantenimiento, buscando su integración con los procesos de gestión de configuración de un activo.

Por otro lado, las contribuciones explicadas en esta sección permiten poner un marco para el diseño, implementación y validación de servicios inteligentes que puedan ser realizados por especialistas en diferentes dominios (ej. diagnóstico de componentes mecánicos, pronóstico, estrategias de mantenimiento), dando de esta manera soporte al trabajo en los capítulos 3 y 4 de este proyecto de tesis.

El trabajo realizado ha evolucionado hacia resultados y productos concretos, especialmente el realizado en el diseño de la plataforma de servicios web, pero también ha dejado abiertas diferentes líneas de investigación, sobre todo relacionadas con una mayor implicación de las tecnologías semánticas en el soporte de la interoperabilidad del mantenimiento (como se explica en la sección 5.2).

2.4 Publicaciones

Revistas y libros

Jantunen, E., Emmanouilidis, C., Arnaiz, A., & Gilabert, E. (2010). Economical and technological prospects for e-maintenance. International Journal of System Assurance Engineering and Management, 1(3), 201-209. (SJR Q3)

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Contribuciones a congresos

Gilabert, E., Conde, E., & Abaunza, J. (2012). A standard-based data model for configuration management and maintenance support. IFAC Proceedings Volumes, 45(31), 139-144

Gilabert, E., Jantunen, E., Emmanouilidis, C., Starr, A., & Arnaiz, A. (2014). Optimizing E-Maintenance Through Intelligent Data Processing Systems. In Engineering Asset Management 2011 (pp. 1-9). Springer London. (SJR Q4)

3 Diagnóstico de fallos

Las estrategias de mantenimiento predictivo son muy eficientes en los modos de fallo mecánicos, cuando la probabilidad de fallo aumenta con el tiempo, y una o más técnicas de monitorización (vibraciones, aceite, termografía, sonido, etc.) pueden predecir el fallo antes de que ocurra. Sin embargo, el uso de estas técnicas siempre se ha relacionado con un tipo muy limitado de activos, donde la falta de disponibilidad puede conducir a una pérdida en seguridad (aeroespacial) o grandes pérdidas económicas (energía).

Uno de los mayores problemas en el mantenimiento predictivo es la necesidad de manejar grandes cantidades de datos y el coste de la capacitación del personal. En numerosas ocasiones, la estructura defectuosa de los datos predictivos dificulta la automatización de las tareas, ya que normalmente hay incertidumbre en el proceso de diagnóstico. Además, algunos modelos de diagnóstico y monitorización deben construirse directamente a partir de los datos, ya que no hay experiencia disponible. Finalmente, hay casos en los que se requiere de una adaptación continua de las soluciones de diagnóstico y monitorización, a medida que aumenta el conocimiento en mantenimiento.

Para hacer frente a estos problemas, se pueden aplicar varios paradigmas de algoritmos provenientes del campo del aprendizaje automático a una variedad de situaciones, y con diversos requisitos y características del problema (Supervisado, no supervisado, aprendizaje por refuerzo, conocimiento experto, minería de datos...).

Por otro lado, las Redes Bayesianas (*Bayesian Networks* – BNs) nos permiten modelar el conocimiento gestionando la incertidumbre y la adaptación. Las BNs junto con otras metodologías de recogida de información utilizadas en ingeniería nos ofrecen la posibilidad de automatizar la tarea de diagnóstico y predicción de fallos. Las técnicas de aprendizaje automático se utilizan ampliamente con el mismo propósito, pero tienen el inconveniente de que necesitan un amplio abanico de datos para poder realzar un modelo fiable, y aun así existe riesgo de excesivo acoplamiento al sistema con el que se realizan las pruebas.

De todas formas, estas técnicas están más enfocadas a la detección de fallos específicos, mientras que el propósito de esta sección no está centrado tanto en la resolución de un problema concreto, sino en la metodología que hay que tener en cuenta y las acciones que hay que llevar a cabo para realizar un buen sistema de diagnóstico en ausencia o escasez de datos, que es lo que ocurre la mayoría de las veces.

Un análisis de modos de fallos y efectos (AMFE) es un procedimiento de análisis de fallos y sus efectos en un sistema. Nos permite estudiar los fallos que podrían producirse y las causas-efectos derivados del modo de fallos previsto. Un AMFE bien diseñado es una fuente de información útil y valiosa, que contiene componentes, fallos en el sistema, las causas de fallo y sus efectos. Esta información, sin embargo, es un documento simple que no puede ser utilizado en otras formas "directas". Si lo transformamos correctamente en una Red Bayesiana se podría utilizar de otras maneras, tales como aplicaciones de software. Mientras que el AMFE se utiliza principalmente para localizar errores de diseño antes de que el sistema esté completamente desplegado, el objetivo de las Redes Bayesianas es ayudar a localizar los problemas antes de que ocurran en el sistema. Además, una Red Bayesiana puede ser útil a la hora de visualizar todas las cadenas de causa-efecto que intervienen en el sistema contenido en el AMFE.

Las Redes Bayesianas son modelos adecuados para las tareas de análisis (en especial, para el diagnóstico) que permiten tratar los problemas de incertidumbre y aprendizaje por medio de la representación causal o la información de dependencia existente entre causas y efectos (o premisas y eventos). Para permitir este tratamiento, la representación de información utiliza redes de conocimiento (no reglas) que se basan en dos teorías que provienen del campo matemático: la teoría de grafos y la teoría de probabilidad [Pearl, 2014].

3.1 Antecedentes

Las acciones de mantenimiento se inician según el estado de un parámetro que generalmente está relacionado con el mal funcionamiento del equipo conocido. Los indicadores típicos son vibraciones, temperaturas, pérdidas de rendimiento, etc. Este mantenimiento se conoce más comúnmente como mantenimiento basado en la condición (CBM) o mantenimiento predictivo (*Predictive Maintenance* – PdM), y el uso de los indicadores anteriores normalmente se conoce como una actividad de *condition monitoring*. Es importante señalar que otras técnicas, como el control estadístico de procesos, también pueden ser de ayuda.

El mantenimiento predictivo busca un análisis mucho más rentable que el mantenimiento preventivo, mejorando la fiabilidad del equipo (evitando fallos inesperados de la maquinaria).

Sin embargo, los métodos de mantenimiento predictivo necesitan grandes cantidades de información para proporcionar una respuesta adecuada a los diferentes subproblemas de detección de fallos: identificación de anomalías, diagnóstico, evaluación de la gravedad del fallo, pronóstico, etc. Todas estas tareas son 'intensivas en conocimiento', ya que existe una evidente necesidad de experiencia para poder manejarlos. Además, la respuesta a problemas anteriores requiere de la inclusión de información de muchas fuentes diferentes (vibraciones, temperatura, aceite, partículas de desgaste, etc.), fuentes que no hace mucho tiempo estaban aisladas.

La incertidumbre aparece en los problemas de diagnóstico a diferentes niveles, que pueden clasificarse como fallos de información y/o modelo [Díez, 2000]. En un espacio problemático como el diagnóstico de fallos por análisis de vibraciones, podemos ver que cuando hablamos de modos de fallo, la frontera entre problemas diferentes a menudo es difusa. Por ejemplo, es difícil determinar si solo hay desalineación o si también hay desequilibrio en una máquina rotativa. En muchos casos, aunque hay una clara diferencia, varios problemas complican esto:

- Es probable que los síntomas de la maquinaria sean una combinación de diferentes problemas (el desequilibrio y la desalineación aparecen muy a menudo, aunque uno de ellos esté en un nivel mínimo)

- La información (ej. los espectros) podría no estar clara. Por ejemplo, la resolución de frecuencia es limitada y según el número de componentes en análisis y el rango espectral, algunas mediciones pueden vincularse a más de un problema.

- En muchos casos, el rango de los dispositivos instalados puede limitar la información, como la capacidad de medir la demodulación en alta frecuencia y la energía de impulsos.

- Los modelos también tienen inexactitudes, debido a la alta dependencia humana al evaluar la gravedad de los picos espectrales. Con respecto a las máquinas herramienta, por ejemplo, casi no hay información sobre los límites máximos superados.

Como resultado, un patrón espectral dado puede estar relacionado con varios problemas, con la incertidumbre vinculada a la interpretación (en casi todos los casos) y por lo tanto, la incertidumbre debe tratarse para resolver los problemas de diagnóstico de manera adecuada.

Otro desafío se relaciona con la necesidad de mantener los sistemas automatizados adaptados. En [Arnaiz & Gilabert, 2004], se indica que una vez que tenemos un sistema basado en el conocimiento, sin importar cómo se haya creado, podemos distinguir entre tres motivaciones básicas para el aprendizaje y el cambio de conocimiento:

- Corrección de errores del sistema (conocimiento adquirido a través de la experiencia y comentarios)
- Mejora de la base de conocimiento (nuevos productos, nuevos medios de análisis)
- Mejora de la base de conocimiento en términos de eficiencia (estrategias dinámicas para la reducción de costes de mantenimiento)

Cabe destacar el hecho de que la actualización de la creencia es, además del mecanismo de inferencia principal, el mecanismo de aprendizaje para los casos de fallo. Por último, es interesante ver cómo la creencia también se relaciona con una función de costes diagnóstico que puede ayudar a decidir entre las acciones correctivas y proactivas.

Por otro lado, en este trabajo describimos cómo hemos utilizado una metodología para crear un sistema de diagnóstico en grandes motores diésel utilizados en buques marinos de carga. Existen diferentes trabajos previos de diagnóstico en aplicaciones de motores diésel. [Bobbio et al., 2001] detallan una metodología para el mapeo de árboles de fallos en Redes Bayesianas. Usando AMFE para hacer el mapeo, utilizando las cadenas de causa-efecto para propagar la creencia. [Yan & Shi-qi, 2007] describe cómo llevar a cabo el análisis del motor diésel basado en la información del lubricante. El trabajo desarrolla un Sistema de Soporte a Decisión capaz de realizar o diagnóstico de diferentes fallos relacionados con el desgaste de los equipos. [Karlsen, 2003] usa emisiones acústicas con el fin de detectar un cambio en la condición, centrándose en el tratamiento de la señal. [Sharkey et al., 2000] investiga la viabilidad de la formación de redes neuronales artificiales (RNA), sobre la base de datos de la presión en el cilindro, para proporcionar una alerta temprana de ciertos fallos conocidas. [Mesbahi, 2001] realiza una validación de sensores inteligentes y la técnica de diagnóstico de fallos en línea para un motor diésel turboalimentado de 6 cilindros.

3.2 Contribuciones

A continuación, se describen las dos contribuciones con relación a este capítulo sobre diagnóstico de fallos: el desarrollo de una Red Bayesiana de diagnóstico para máquina herramienta basándose en la información del espectro de vibraciones; una metodología que automatiza la generación de modelos de diagnóstico con incertidumbre y aprendizaje, mediante la combinación de las características y propiedades de un Análisis de Modos de Fallos y Efectos (AMFE) y de las Redes Bayesianas.

3.2.1 Red Bayesiana para diagnóstico por vibraciones

Una Red Bayesiana [Jensen, 2001] es un modelo compacto de representación para razonar bajo incertidumbre. Refleja los estados de alguna parte de un mundo que se está modelando y describe cómo se relacionan esos estados a través de probabilidades condicionales. En aplicaciones de diagnóstico de fallos mecánicos, consiste en una serie de entidades o eventos, representados como variables aleatorias. Una variable aleatoria puede, por ejemplo, representar el evento de que una pieza de hardware mecánico en una instalación de producción haya fallado. Las variables aleatorias que representan diferentes eventos están conectadas por arcos dirigidos para describir las relaciones de dependencia directa entre eventos. La incertidumbre del dominio del problema se representa a través de probabilidades condicionales. Por lo tanto, una Red Bayesiana consta de una parte cualitativa, que describe las relaciones de dependencia del dominio del problema, y una parte cuantitativa, que describe nuestra creencia sobre las fortalezas de las relaciones.

En el prototipo de red de la Figura 17, la relación cualitativa indicada por la dirección de las flechas de enlace corresponde a la dependencia e independencia entre eventos, de forma que la variable a la que apunta un arco es dependiente de la que está en el origen de éste. Por otro lado, las relaciones cuantitativas entre nodos se definen mediante tablas de probabilidad condicional (ver Tabla 6).

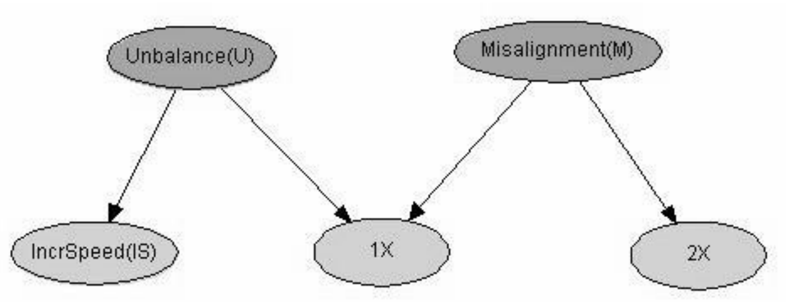

Figura 17. Ejemplo de Red Bayesiana

Tabla 6. Probabilidades de fallo asociados a maquinaria rotativa

Causa de fallo	**A priori**	**Prob. frecuencia**			**Prob. dirección**		**Incr. Amplitud**	
		1X	2X	>2X	Radial	Axial	Velocidad	Carga
Desequilibrio	40	99			90	10	90	
Husillo doblado	10	90	10		20	80	90	
Desalin. Angular	30	70	20	10	20	80		90
Desalin. Paralelo	30	20	70	10	80	20		90
Pérdida mecánica	5		80	20	90	10		
(Otras causas)		20	30	50	50	50	25	25

Podemos ver en la Figura 17, un grafo dirigido acíclico (*Directed Acyclic Graph* – DAG) donde cada arco está dirigido y no hay ciclos. Contiene 5 nodos (variables aleatorias discretas) que corresponden a diferentes estados que pueden ocurrir en nuestro sistema: Desequilibrio(U), Desalineamiento(M), Incremento de amplitud en vibraciones cuando incrementa la velocidad (IS), Picos de amplitud altos en la frecuencia fundamental (1X) y Picos de amplitud altos en 2ª armónica (2X). Esta representación gráfica sirve para representar las suposiciones dependientes e independientes, que encamina a desarrollar una distribución de probabilidad conjunta. Por ejemplo, podemos decir que 2X es condicionalmente dependiente de M, pero es condicionalmente independiente de U dado M.

Es decir, $P(2X/U, M) = P(2X/M)$

Podemos decir también que 1X y 2X son condicionalmente independientes bajo un fallo de un eje dado.

Es decir, $P(1X|M, 2X) = P(1X|M)$

Por teoría de la probabilidad, sabemos que podemos inferir muchas probabilidades P (2X| M) = P(M) · P(M|2X)/P(2X) mediante el uso del teorema de Bayes y las probabilidades condicionales. Esto se usa para inferir la probabilidad de que la Desalineación (M) tenga evidencia de la aparición de un pico de amplitud en el segundo armónico (2X), pero también puede funcionar en la dirección opuesta, lo que lo hace útil, por ejemplo, para reforzar otras causas (como Desequilibrio) si ya sabemos que no hay Desalineación en el sistema. Mediante los mecanismos de inferencia apropiados, la gestión de las distribuciones condicionales parciales permite el cálculo de probabilidades para cualquier nodo en la red dada cualquier evidencia.

La adaptación es el proceso de refinar las probabilidades condicionales especificadas para una Red Bayesiana teniendo en cuenta los resultados reales del experimento. Este es probablemente el tipo de mecanismo de aprendizaje más interesante que se puede utilizar en el diagnóstico de maquinaria, ya que el aporte más importante (en términos de aprendizaje) se debe esperar del uso local de las herramientas automatizadas, siempre que comiencen a aplicarse en mantenimiento y sistemas de diagnóstico. Por ejemplo, cada vez que se diagnostica una máquina, la información sobre sus síntomas y problemas se puede utilizar para adaptar las probabilidades de la red. Este enfoque se ha utilizado en la Red Bayesiana para diagnosticar máquinas herramientas.

El ejemplo más simple es que en referencia a las tablas de actualización fraccionaria, donde una tarea estadística está destinada a modificar las estimaciones de los parámetros gradualmente con los casos utilizados. Podemos considerar la tabla de probabilidad condicional (*Conditional Probability Table* – CPT) de Desequilibrio, es decir, la probabilidad previa de tener desequilibrio en un tipo de maquinaria determinado cada vez que se detecta una anomalía (ver Tabla 7).

Tabla 7. Probabilidad a priori de Desequilibrio

Desequilibrio	
False	0,60
True	0,40

Está claro que esta relación puede no reflejar casos particulares en diferentes entornos. Por ejemplo, una empresa determinada puede presentar una tasa muy alta de anomalías relacionadas con este problema. Podemos agregar una nueva característica en esta tabla de probabilidad condicional, llamada "experiencia", representada por un número que indica el valor que asignamos a la experiencia en el diseño "a-priori". Ahora, también podemos incluir comentarios de la aplicación del sistema. Por ejemplo, podemos suponer que nuestra creencia en la corrección de la distribución condicional actual para el desequilibrio es baja, por lo que podemos establecer el recuento de experiencia inicial en un número pequeño, digamos 10 (ver Tabla 8).

Tabla 8. Probabilidad a priori de Desequilibrio con experiencia

Desequilibrio	
False	0,60
True	0,40
Experiencia	10

Ahora, si recibimos retroalimentación de 5 casos nuevos (supongamos que en todos ellos se encuentran pruebas de desequilibrio) y volvemos al CPT de desequilibrio, veremos un valor de experiencia de 15. Estos 5 recuentos adicionales pertenecen a todos los estados "True". Por lo tanto, la distribución de probabilidad adaptada de Desequilibrio se convierte en:

$$P(Desequilibrio) = \frac{N(True)}{Experiencia} \quad (1)$$

donde N(True) indica el número de eventos verdaderos registrados hasta el momento, lo que representa 5 en las últimas 5 observaciones, más 4 en las primeras 10 observaciones (0,40 * 10). Es decir:

$$P(Desequilibrio) = \frac{(0.40 \cdot 10) + 5}{15} = 0.6 \quad (2)$$

Esto ofrece como resultado la CPT que podemos ver en la Tabla 9.

Tabla 9. Probabilidad a priori de Desequilibrio con experiencia (2)

Unbalance	
False	0.40
True	0.60
Experience	15

Para resumir, un paso de adaptación consiste en ingresar evidencia, propagar y actualizar (adaptar) las tablas de probabilidad condicional y las tablas de experiencia. El procedimiento de adaptación anterior otorga el mismo peso a las experiencias recientes y a las anteriores. A veces, sin embargo, las observaciones antiguas no cuentan tanto como las más recientes. Por lo tanto, tenemos que desaprender u olvidar algunos de ellos. Esto es lo mismo que decir que las nuevas observaciones (evidencia) son más importantes que las anteriores y, por lo tanto, deberían tener más peso. Además, la actualización fraccional tiene un problema de sobreestimación de la importancia de los recuentos, por lo que los recuentos pueden hacer que los parámetros en CPT sean demasiado resistentes al cambio.

Dichas situaciones se pueden superar mediante tablas de desvanecimiento (*fading*), que representan la velocidad a la que se olvidan las observaciones anteriores. Por lo tanto, con un valor de desvanecimiento intermedio de 0,5 y un nuevo caso verdadero de desequilibrio, tenemos un cambio muy significativo con solo una observación.

$$P(Desequilibrio) = \frac{\big(Fading \cdot N(True)\big) + 1}{(Fading \cdot Experience) + 1)} = \frac{0.5 \cdot (0.40 \cdot 10) + 1}{6} = 0.5 \qquad (3)$$

Con estos principios, durante este trabajo de investigación fue desarrollada una Red Bayesiana de diagnóstico para máquina herramienta basándose en la información entraría del espectro de vibraciones. La Red Bayesiana fue integrada en TESSnet, que es una plataforma web que se puede usar como Sistema de Gestión de Mantenimiento Predictivo (*Predictive Maintenance Management System* -PMMS) (Figura 18). Es posible acceder a la información de la empresa y la planta desde el sitio web, junto con el estado de la máquina y el componente, y también se almacena la información del sensor y las medidas.

TESSnet puede visualizar valores de parámetros específicos, junto con gráficos de tendencias. Utilizando estas tendencias y estableciendo valores máximos y mínimos para los parámetros, la plataforma proporciona un pronóstico de los ensamblajes en términos de la vida útil restante. El diagnóstico se proporciona con un sistema basado en reglas, por ejemplo, si el parámetro X supera el valor de advertencia, la posible causa es Y.

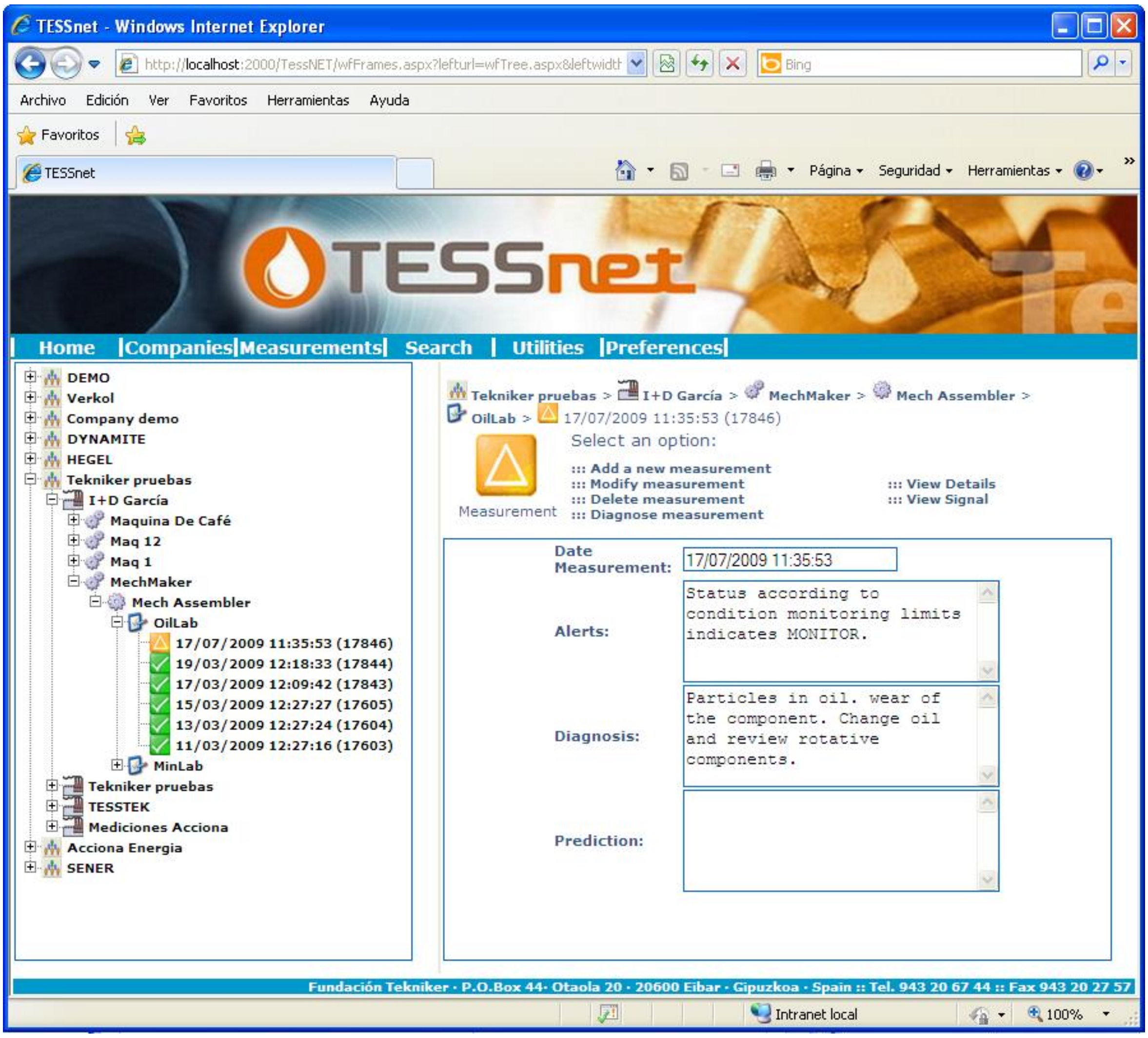

Figura 18. Plataforma web TESSnet

La Red Bayesiana complementa el sistema basado en reglas. El principal inconveniente es que cada sistema requeriría su Red Bayesiana específica, ya que TESSnet contiene información sobre diferentes sistemas como aerogeneradores o máquinas herramientas. Sin embargo, para sistemas similares podría ser posible crear fácilmente una nueva Red Bayesiana, cambiando algunos parámetros o probabilidades, ajustándolos al nuevo sistema.

3.2.2 Metodología de AMFE a Red Bayesiana

La principal contribución se basa en una metodología que automatiza la generación de modelos de diagnóstico. Para ello se apoya en la combinación de las características y propiedades de los siguientes fundamentos teóricos:

- Análisis de Modos de Fallos y Efectos (AMFE), que recogen la información de fallos de una forma estructurada

- Redes Bayesianas, que permiten la generación del modelo de diagnóstico con incertidumbre y aprendizaje

A partir de ellos definimos una metodología para la creación de un sistema de diagnóstico, la cual se ha aplicado en motores diésel de buques marinos de carga. La metodología que hemos empleado para hacer su mapear la Red Bayesiana es "de abajo a arriba" (*bottom-up*), comenzando con los componentes individuales y sus subsistemas y finalizando con el sistema completo. Los tipos de nodos que hemos utilizado son: Fallos, Fallo de componente y Efecto. Los nodos de fallo representan un fallo general en el sistema mientras que los fallos de componentes representan un fallo específico sobre un componente. Los efectos son los resultados de un fallo (general o de componente) los cuales no causan más fallos en niveles inferiores, es decir, los nodos hoja. Un cuarto tipo de nodo (Componente) es usado para localizar en qué componente está ocurriendo el fallo.

Los pasos para construir la red deberían ser:

1. Comenzar con los fallos de componentes. Añadimos los fallos de componentes a la red como nodos.

2. Añadir los modos de fallos de componentes. Los modos de fallo de componentes deberían tener arcos apuntando a cada nodo de fallo de componente. Esto identifica los modos de fallo como instancias específicas de los fallos de componente. También la dirección del arco puede ser la contraria. En este caso los modos de fallo serían el centro de la red en lugar de los nodos de fallo de componentes.

3. Añadir los efectos de modo de fallo. Añadir los efectos de cada modo de fallo con flechas apuntando desde el modo de fallo al efecto

4. Juntar nodos comunes

    a. Efectos comunes. Juntar los efectos comunes de los diferentes modos de fallo en un fallo común.

    b. Causas comunes. Juntar las causas comunes de diferentes modos de fallo.

c. Juntar relaciones causa-efecto. Juntar el efecto de un modo de fallo como una causa de otro fallo, de manera que el arco apunte desde el efecto a la causa del otro modo de fallo.

d. Juntar fallos de componentes. Un modo de fallo puede ser la causa de otro modo de fallo.

Para comprender mejor el proceso, indicamos un ejemplo paso a paso. La Tabla 10 muestra el AMFE que usaremos en nuestro ejemplo. La tabla contiene cadenas de causas y efectos relativas a un motor diésel: inyector, cilindro y pistón. Desde la Figura 19 hasta la Figura 23 se muestran los pasos de añadir nodos. La Figura 24 muestra la fusión entre distintas causas y efectos de fallo.

Tabla 10. Ejemplo de AMFE

Fallo de componente	**Modo de fallo**	**Causa**	**Efecto**
Inyector	Mala inyección	Aguja atascada	Mala lubricación
			Pistón perforado
Cilindro lineal	Mala lubricación	Mala inyección	Sobrecalentamiento
		Mala calidad de aceite	Corte de Pistón
Pistón	Pistón perforado	Mala inyección	Partículas de desgaste
	Pistón Cortado	Sobrecalenta miento	Partículas perforantes
		Mala lubricación	

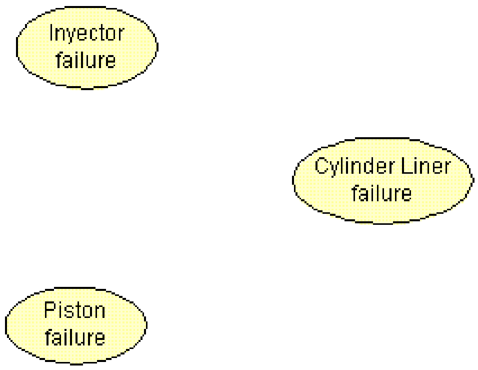

Figura 19. Añadiendo nodos de fallos

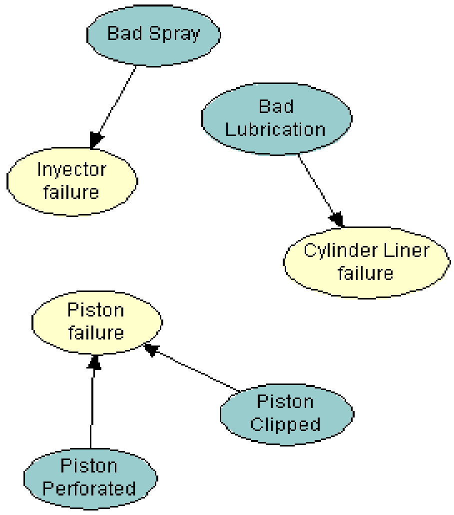

Figura 20. Añadiendo modos de fallo

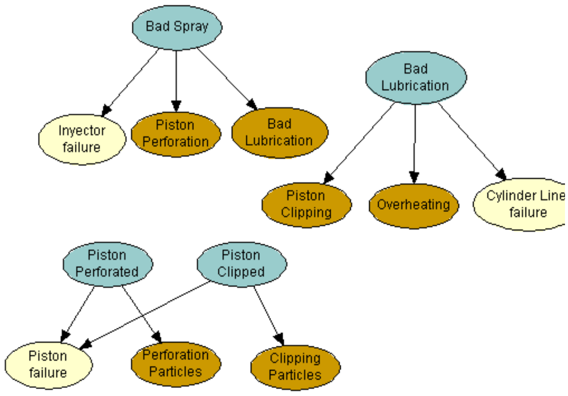

Figura 21. Añadiendo nodos efectos

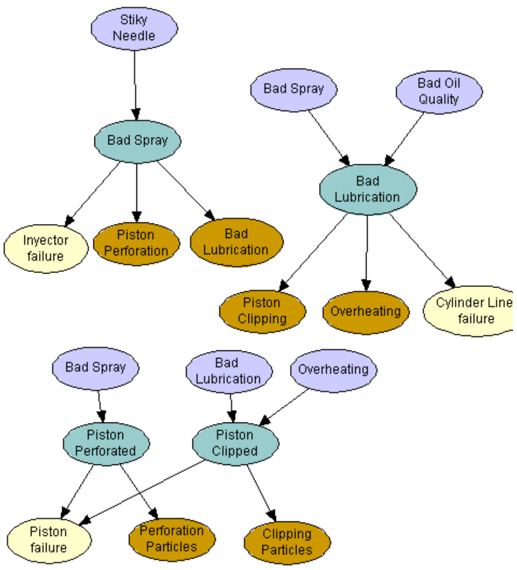

Figura 22. Añadiendo nodos causa

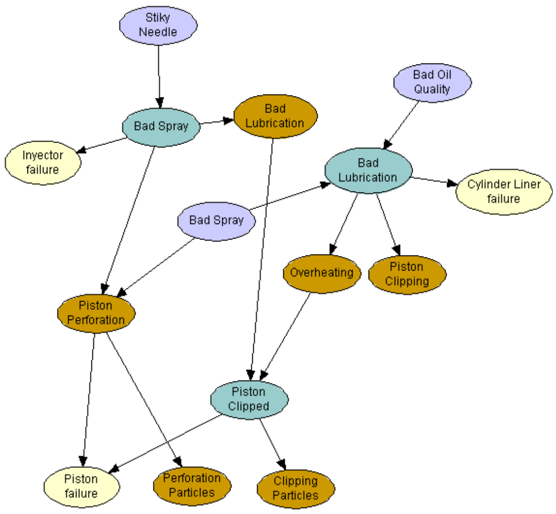

Figura 23. Uniendo nodos causa y efectos

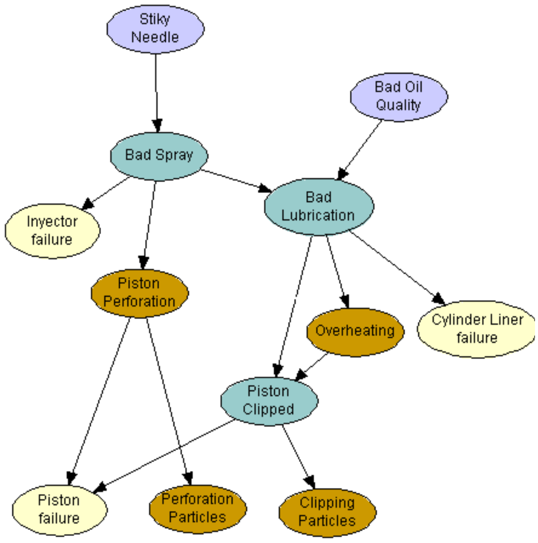

Figura 24. Uniendo fallos y causas

La asignación de probabilidades a los arcos y nodos es la parte más compleja de la metodología. Los nodos de la red se consideran de tipo booleano, es decir, el fallo ocurre o no, el efecto es visible o no, el componente funciona o no. Las probabilidades son asignadas a los nodos dependiendo de cómo ocurre el fallo.

La ratio de ocurrencia del AMFE debería ser utilizado para asignar las probabilidades de los nodos. La ratio es ordinal, no lineal, lo que quiere decir que una ratio de ocurrencia de 8 es más probable que 4, pero eso no significa que sea el doble de probable. Además, no está estandarizado, de manera que cada AMFE puede asignar las ratios de ocurrencia de diferente forma. Por ejemplo, una ratio de ocurrencia de 5 podría ser una probabilidad de 0,1 a 0,001, dependiendo del AMFE.

Tabla 11. Tabla de probabilidad de pistón (OR binario)

Pistón Perforado	Verdadero		Falso	
Pistón Cortado	Verdadero	Falso	Verdadero	Falso
Fallo	1	1	1	0
Normal	0	0	0	1

Por otro lado, el AMFE no contiene información sobre las probabilidades de las causas de fallo. Los nodos causa son nodos que no tienen ninguna dependencia. En el AMFE de la Tabla 10, la ratio de ocurrencia para asignar la probabilidad de '*Bad spray*' debido a '*sticky needle*' podría usarse, pero la probabilidad de que la "aguja" esté "pegajosa" es desconocida. Estos valores de probabilidad deberían ser ajustados en estudios previos, con datos extras, o con la opinión de los expertos.

Los nodos que son dependientes de más de un padre actúan de forma diferente dependiendo de su tipo. La mayoría de estos fallos ocurren cuando una o más de sus causas se presentan. Las puertas *Noisy-OR* son usadas para esto, que son una generalización de las puertas *OR* binarias. Si un fallo tiene n posibles causas, la causa x_i tiene una probabilidad de p_i, que es la probabilidad de que el fallo ocurra cuando existe la causa x_i y no hay otras causas.

$$p_i = P(Fallo\ |x_i\ sólo) = P(Fallo\ |\overline{x_1}, \overline{x_2}, \dots, x_i, \dots, \overline{x_n}) \quad (4)$$

La probabilidad de cualquier combinación de causas activas es calculada por la siguiente ecuación:

$$P(Fallo\ |x_i, x_2, \dots, x_n) = 1 - (1 - p_1) \cdot (1 - p_2) \cdot \dots \cdot (1 - p_n)$$
$$P(Fallo\ |X) = 1 - \prod (1 - p_i)\ donde\ X = Todas\ las\ causas\ acticas\ x_i \quad (5)$$

La Tabla 11 y la Tabla 12 muestran la diferencia entre usar las puertas *OR* y *Noisy-OR*, detallando las tablas de probabilidad para el nodo Pistón de la Tabla 10.

Tabla 12. Tabla de probabilidad de pistón (*Noisy-OR*)

Pistón Perforado	Verdadero		Falso	
Pistón Cortado	Verdadero	Falso	Verdadero	Falso
Fallo	0.98	0.9	0.8	0
Normal	0.02	0.1	0.2	1

Algunos fallos pueden necesitar simultáneamente más de una causa para que ocurran. Las puertas *Noisy-AND* se definen usando las mismas consideraciones que las puestas *OR*. En este caso cada una de las probabilidades p_i se definen por la probabilidad de que el fallo ocurra cuando todas las causas excepto por x_i ocurren.

$$p_i = P(Fallo \mid Todas\ excepto\ x_i) = P(Fallo\ |x_1, x_2, \ldots, \overline{x_i}, \ldots, x_n) \tag{6}$$

La probabilidad de cualquier combinación de causas activas se calcula entonces por la siguiente ecuación:

$$P(Fallo\ |x_i, x_2, \ldots, x_n) = p_1 \cdot p_2 \cdot \ldots \cdot p_n$$
$$P(Fallo\ |X) = \prod p_i\ donde\ X = Todas\ las\ causas\ activas\ de\ x_i \tag{7}$$

La Tabla 13 muestra la probabilidad si consideramos que un pistón tiene que estar perforado y cortado para que resulte defectuoso.

Tabla 13. Tabla de probabilidad de pistón (*Noisy-AND*)

Pistón Perforado	Verdadero		Falso	
Pistón Cortado	Verdadero	Falso	Verdadero	Falso
Fallo	0.72	0.9	0.8	0
Normal	0.28	0.1	0.2	1

Las puertas *Noisy-OR* trabajan bajo la suposición de que todas las causas posibles de que ocurra un fallo se conocen previamente. Esto no es siempre posible ya que puede haber causas desconocidas que no hayan sido registradas en el AMFE.

Un parámetro adicional llamado *pérdida* se añade para arreglar esto. Una pérdida consiste en una categoría residual "Otros", representando lo que no es explícito en el AMFE, y hace posible que los fallos ocurran si ninguna de las causas registradas está presente.

Para usar las puertas *Noisy-OR* y las *AND*, la probabilidad de que los fallos ocurran para cada una de las causas necesita ser conocida. Cuando las probabilidades son desconocidas, no hay forma de saber qué causa tiene más relevancia para que el fallo ocurra. La solución es el uso de la teoría de Máxima Entropía (ME). La teoría ME expone que, en ausencia de cualquier información, todos los estados de fallo s de una variable X deberían asignarse a la misma probabilidad de (1/s), como mostramos en la Tabla 14.

Todos los valores de probabilidad pueden ser posteriormente editados a valores específicos, que pueden ser obtenidos de información extra de diseño, expertos, ensayos de fiabilidad, y evaluaciones de ejecución en campo.

Algunas veces, diferentes variables pueden ser consideradas como distintos grados de una variable común. Por ejemplo, los nodos “Sin salida de energía” y “Salida de energía insuficiente” se pueden considerar diferentes estados de salida de energía de un motor. En lugar de usar 2 nodos booleanos, es posible utilizar una variable llamada “Salida de energía” con estados Normal, Pobre y Ninguno. Usando este tipo de variables multi-estado podemos construir redes más pequeñas, aunque con tablas de probabilidad más complejas.

Tabla 14. Tabla de Máxima Entropía en un nodo con 3 causas

Nodo 1	Verdadero				Verdadero			
Nodo 2	Verdadero		Falso		Verdadero		Falso	
Nodo 3	Verdadero	Falso	Verdadero	Falso	Verdadero	Falso	Verdadero	Falso
Verdadero	1	0.66	0.66	0.33	0.66	0.33	0.33	0
Falso	0	0.33	0.33	0.66	0.33	0.66	0.66	1

Una vez creada la Red Bayesiana, puede ser utilizada en más de una forma. En este trabajo de investigación la hemos utilizado para crear un sistema de diagnóstico en grandes motores diésel utilizados en buques marinos de carga. Una serie de parámetros del aceite lubricante se analizaron con el fin de ejecutar un diagnóstico sobre el estado del motor, parámetros tales como la viscosidad, las partículas y el contenido insoluble, carbonilla, etc. Algunos fallos hacen que estos parámetros se incrementen, como por ejemplo, la combustión incompleta incrementará la carbonilla, el recorte del pistón y la perforación incrementará el número de partículas de recorte y perforación en el aceite, y así sucesivamente.

Todos estos valores de los parámetros de aceite se almacenan en una base de datos, en el que se utilizará más adelante en ambas aplicaciones. Con el fin de realizar el diagnóstico la aplicación realiza los siguientes pasos (Figura 25):

1. Recuperar los datos del sensor de la base de datos. La aplicación se conectará y recuperar las últimas mediciones realizadas por el sensor.

2. Discretizar los valores numéricos. La Red Bayesiana utiliza valores discretos, así que en primer lugar es necesario convertir los valores numéricos en los discretos. Los valores máximo y mínimo se pueden utilizar para esto. Por ejemplo, si la concentración de hollín es superior al 50%, el estado de hollín se establece en Verdadero.

3. Propagar la creencia. Los valores booleanos se asignan a los nodos de parámetros, entonces la creencia se propaga en la red.

4. Devolver datos desde los nodos fallo. Una vez que la propagación se ha completado, los valores de creencias actualizadas de los nodos de fallo se recuperan.

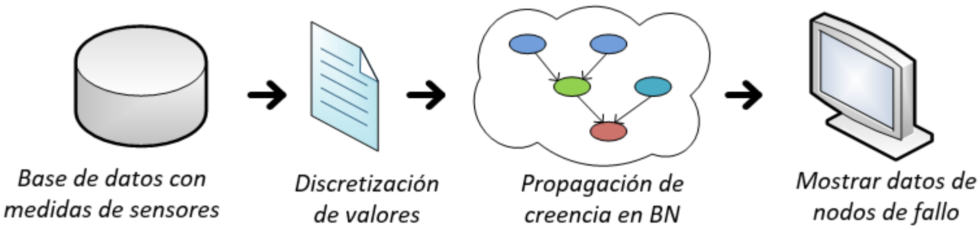

Figura 25. Flujo de información en la aplicación

De esta manera la captura de datos y el diagnóstico trabajan de forma asíncrona e independiente. Se puede utilizar otro tipo de sensores para obtener información adicional (vibraciones, temperatura, etc.).

La Red Bayesiana se ha creado con la herramienta HUGIN Expert [Madsen et al., 2003](ver Figura 26). HUGIN Expert proporciona una interfaz de creación de Redes Bayesianas y el software de diseño, así como *plug-ins* para integrar sus funciones con diferentes plataformas y lenguajes de programación.

Para el uso de la Red Bayesiana, se ha implementado una aplicación independiente específicamente para diagnosticar el estado de un motor diésel marino (ver Figura 27). Cuando se pulsa el botón, la última medición se recupera de una base de datos, junto con los valores de sus parámetros. Estos parámetros son discretizados y asignados a la red. Una vez que la creencia se propaga a través de la red, los modos de fallo y el estado de los componentes se muestra, tanto numéricamente como en un tipo de color (normal, advertencia y peligro).

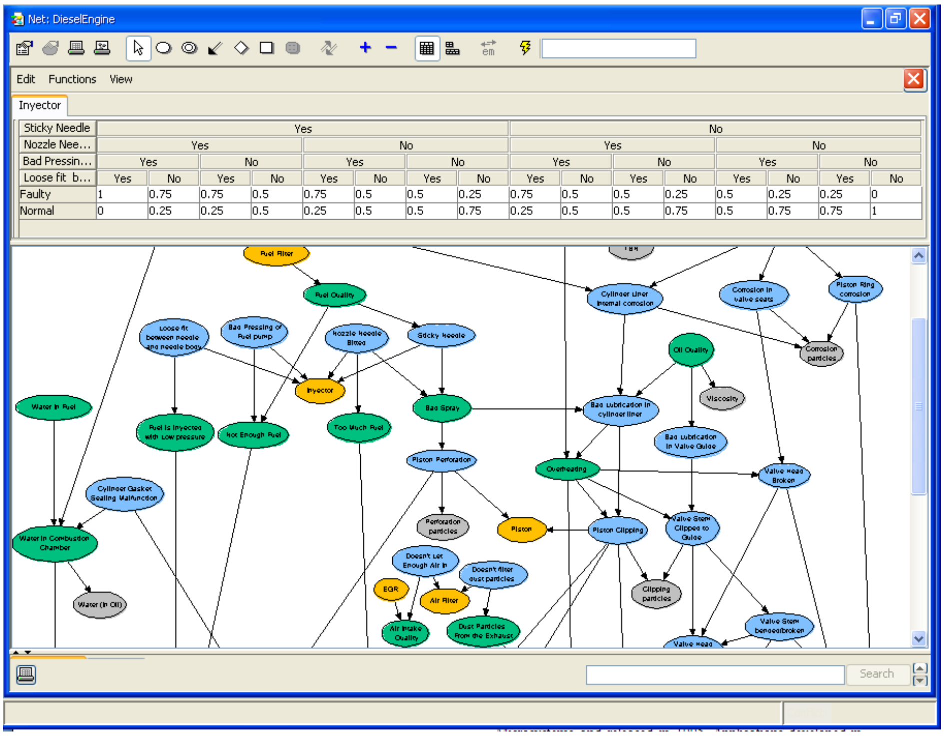

Figura 26: HUGIN Expert software

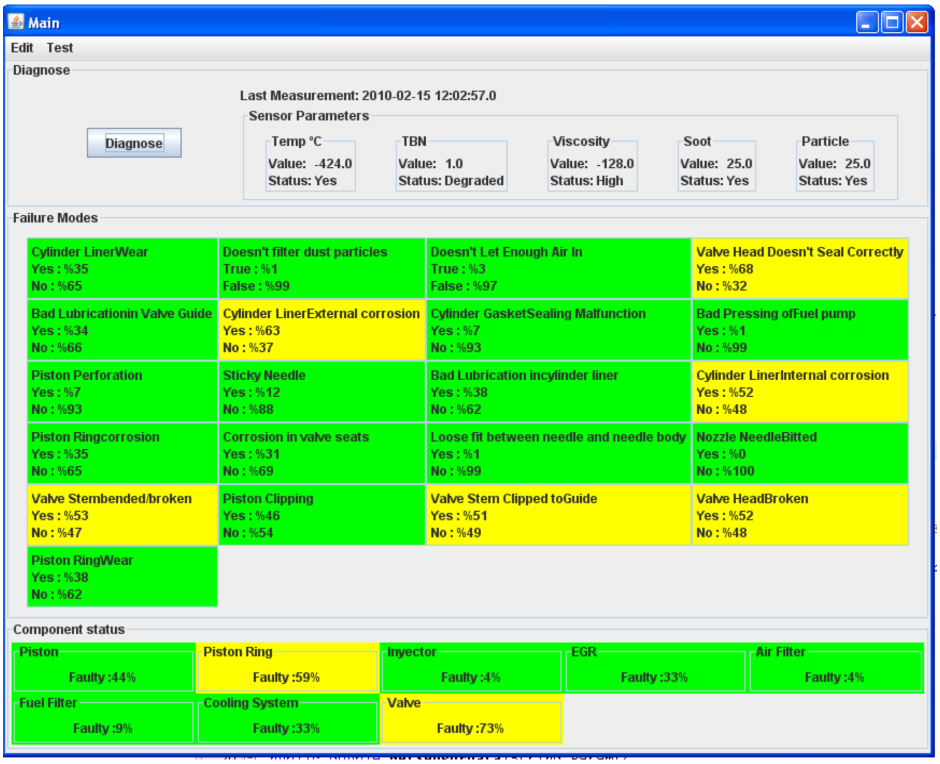

Figura 27: Aplicación de diagnóstico de motor diésel

3.3 Conclusiones y trabajo futuro

Este trabajo de investigación expone las necesidades que surgen dentro de la aplicación de sistemas inteligentes para el mantenimiento de activos industriales. Estos problemas han permitido identificar procesos de aprendizaje que pueden ser necesarios para complementar y apoyar los procesos inferenciales. El despliegue completo y las pruebas de las capacidades de aprendizaje se realizan con la herramienta HUGIN, que incluye los algoritmos necesarios para implementar el sistema de aprendizaje. El aprendizaje puede considerarse como la verdadera característica que hace que un sistema parezca un dispositivo inteligente, evitando automáticamente la ocurrencia repetitiva de errores fácilmente evitables. Observamos que las Redes Bayesianas son algoritmos dignos de ser considerados dentro del área de diagnóstico y detección de fallos. Incluimos un prototipo que muestra cómo adaptar un sistema ya construido con información parcial proveniente de conjuntos de muestras incompletos.

Sin embargo, hay algunos problemas que deberían dedicar trabajo adicional, más allá del alcance de las actividades actuales. La recopilación de muestras de datos apropiadas es una necesidad meticulosa, para garantizar adecuadamente que cualquier modelo funcione correctamente. La validación se realizó utilizando los datos recopilados de varias máquinas durante la etapa de análisis de datos, y algunas pruebas más que provienen de la prueba piloto.

En conclusión, podemos decir que existe la necesidad de desarrollar sistemas adaptativos que puedan mejorar el soporte de software para decisiones de mantenimiento en muchos campos de aplicación además de máquinas herramienta y elevadores. El trabajo que se muestra en este documento es una buena alternativa para proporcionar los mecanismos de adaptación necesarios.

Por otro lado, el método que se explica de diagnóstico de fallos en este proyecto de tesis proporciona una cierta ayuda en la tarea de construir la Red Bayesiana a partir de un AMFE. El AMFE por lo general tiene buena información acerca de las cadenas de causa-efecto, pero falta información probabilística apropiada, por lo que la red resultante será de estructura fija y sin las probabilidades. En este proyecto de tesis se ha descrito un mecanismo para resolver la falta de información de probabilidades, y el desarrollo de una Red Bayesiana para motores diésel marinos, que se ha utilizado en un software desarrollado en JAVA.

La versión actual de la aplicación incluye una interfaz de prueba, que permite al usuario probar todas las posibles combinaciones de entrada de la red y su influencia en todos los nodos de la red. Las futuras versiones de la aplicación pueden incluir un servicio de pronóstico, utilizando las tendencias desarrolladas a partir de un conjunto de mediciones anteriores, y la posibilidad de configurar las dos entradas de sensor y los nodos mostrados. También se considera la posibilidad algoritmo de usar técnicas de aprendizaje automático para aprender la estructura de la Red Bayesiana.

3.4 Publicaciones

Revistas y Libros

García, A., & Gilabert, E. (2011). Mapping FMEA into Bayesian networks. International Journal of Performability Engineering, 7(6), 525-537. (SJR Q2)

Gilabert, E. and García, A. (2011) An e-maintenance architecture for diagnosis automation. In Maintenance Modelling and Applications, edited by John Andrews, Christophe Bérenger and Lisa Jackson, An ESReDA Project Group Report, Det Norske Veritas (DNV) editorial, chapter 5, pp. 443-453.

Contribuciones a congresos

Arnaiz A., E. Gilabert E. (2004) Use of probabilistic expert systems for application in maintenance & diagnosis. A technology to manage uncertainty and adaptation. Workshop proceedings of 17th conference on Euromaintenance, pp 305-31, AEM, Barcelona.

4 Simulación de estrategias y optimización de la planificación

El objetivo principal de este capítulo es centrarse en tecnologías que permitan optimizar las estrategias de mantenimiento, ya sea con diseños más fiables o mediante la mejora en las decisiones de mantenimiento. El análisis de coste-efectividad es clave porque es la forma de indicar si cualquier beneficio o ventaja competitiva se puede lograr mediante el uso de estrategias adecuadas de mantenimiento, especialmente con una orientación al mantenimiento predictivo. El uso de simulaciones en este ámbito ayuda a la toma de decisiones a la hora de seleccionar una estrategia de mantenimiento adecuada para el activo.

En general, las técnicas de análisis de datos nos permiten mejorar la forma en que gestionamos nuestro negocio. Específicamente, a través de la aplicación de análisis descriptivos podemos comprender con más detalle el estado actual del negocio, y el análisis predictivo estima lo que no sabemos. Finalmente, existe un tercer nivel de análisis como una extensión natural de estos procesos, análisis prescriptivo, que conduce a la integración completa con el negocio. El análisis prescriptivo considera no solo los datos comerciales, sino también cómo las decisiones afectan las cuentas de costes y beneficios, y qué restricciones y consideraciones deben considerarse en las acciones que se llevarán a cabo. Esto genera automáticamente políticas de acción realistas que tienen un impacto directo en los beneficios. Mediante el uso de técnicas prescriptivas podemos mejorar la planificación del mantenimiento, reduciendo los tiempos y costes para realizar las tareas en un parque de activos.

El concepto de analítica prescriptiva se hace plenamente patente en esta sección en base a la combinación de acciones predictivas (ej. predecir un fallo) simulación del coste-beneficio de diferentes decisiones relacionadas (ej. diferentes opciones de mantenimiento) y la búsqueda de la mejor decisión (o del conjunto de decisiones para una flota de activos).

4.1 Antecedentes

La analítica prescriptiva se extiende más allá de la analítica predictiva al especificar tanto las acciones necesarias para lograr los resultados previstos como los efectos interrelacionados de cada decisión Está relacionada con el análisis descriptivo y predictivo de los datos, pero enfocándose en explorar un conjunto de acciones y realizar sugerencias, es decir, guiando la toma de decisiones con el fin de encontrar una solución óptima. Aunque la decisión final depende siempre de la persona responsable, la analítica prescriptiva proporciona medios confiables para optimizar las necesidades del negocio y la resolución de problemas.

La analítica prescriptiva permite tomar decisiones en tiempo real y mejorar los niveles de calidad y eficiencia hacia la Industria 4.0, que abarca grandes datos, ciencias matemáticas, aprendizaje automático y otras tecnologías para hacer predicciones y sugerir opciones de decisiones para aprovechar las predicciones (Figura 28).

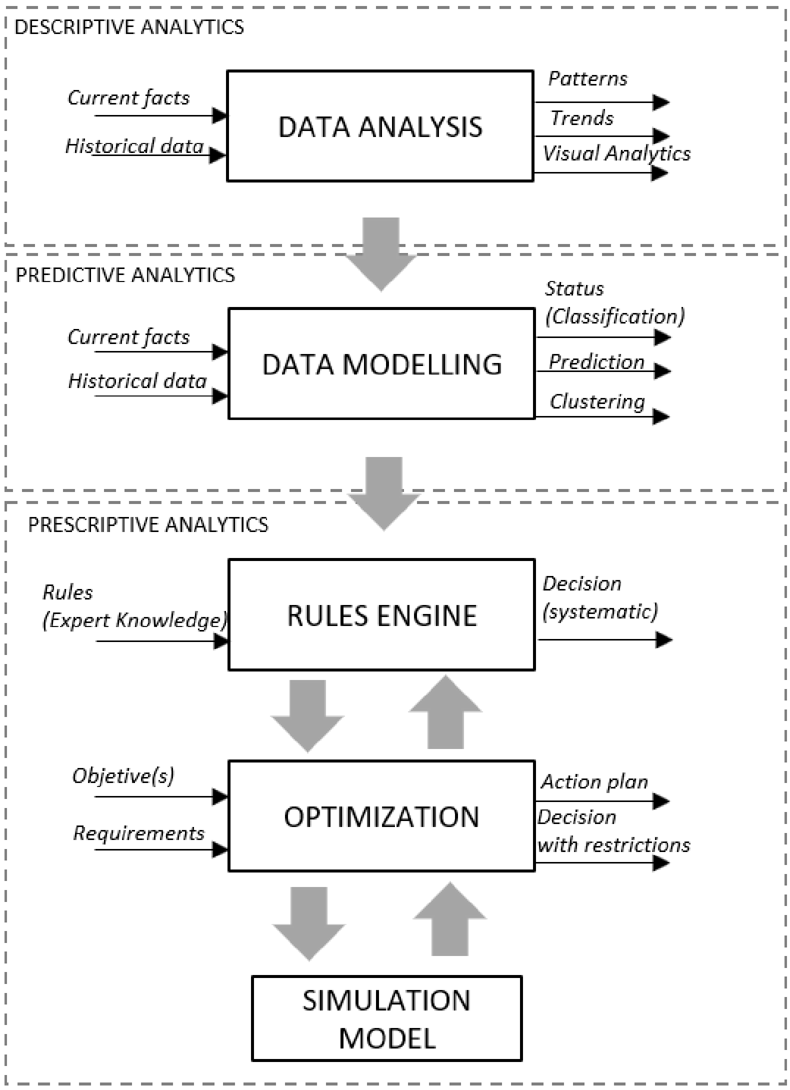

Figura 28. Técnicas de Analítica Prescriptiva y su apoyo en Analítica Descriptiva y Predictiva

El análisis prescriptivo considera no solo los datos comerciales, sino también cómo las decisiones afectan las cuentas de costes y beneficios, y qué restricciones y consideraciones deben considerarse en las acciones que se llevarán a cabo. Da la opción de estrategias de acción realistas que tienen un impacto directo en los beneficios.

En muchos casos el proceso de decisión no es sistemático, sino que la decisión a tomar se enmarca en un contexto definido por una serie de restricciones. Estas restricciones establecen las condiciones para que una decisión sea válida, pero hay muchas decisiones válidas en el mismo contexto. Por lo general, al tomar estas decisiones, existe una forma implícita de evaluar la calidad de una decisión sobre otra, una función objetiva que permite distinguir entre una solución válida mejor que otra.

Por otro lado, la investigación y desarrollo en mantenimiento están ganando importancia en todo el mundo debido a la irrupción de las tecnologías que permiten soluciones avanzadas de mantenimiento, incluidas las técnicas de análisis prescriptivo. La gestión del mantenimiento implica diferentes conceptos y actividades [Garg & Deshmukh, 2006]. Parte de la literatura trata sobre:

a) El desarrollo y la selección de estrategias de mantenimiento óptimas [Bevilacqua & Braglia, 2000] [Christer, 1999] [Gilabert et al., 2015] [Koren & Ulsoy, 2002].

b) El modelado y la programación del mantenimiento de la máquina [Duffuaa, 2000].

c) La teoría de la fiabilidad, el reemplazo y la determinación de la frecuencia de inspección [Jardine, 2001].

d) Simulaciones para medir un sistema de mantenimiento [Banks, 2005] [Barros et al., 2003].

La metodología para el desarrollo de estrategias de mantenimiento está basada en criterios económicos y de fiabilidad, cuyo objetivo final es llegar a una demostración de las mejoras que se pueden obtener mediante las estrategias basadas en condición o predictivas. La mayoría de las veces no se dispone de datos suficientes para una primera aproximación de la mejor estrategia de mantenimiento. Para ello existen herramientas de simulación que permiten aproximar con pocos datos cuál puede ser la mejor estrategia de mantenimiento para un activo o elemento.

El objetivo es reducir los costes de mantenimiento con diseños más fiables y optimización en las decisiones de mantenimiento. La importancia de un análisis de coste-efectividad es clave porque es la forma de indicar si cualquier beneficio o ventaja competitiva se puede lograr mediante el uso de las tareas de mantenimiento más automatizadas, especialmente el mantenimiento predictivo. Existen diversos trabajos en la selección de estrategias para diferentes activos [Watson et al., 2007][Bertling et al., 2005][Kishk et al., 2006].

En el caso del mantenimiento basado en la oportunidad, la idea detrás de esta optimización es aprovechar los momentos de baja producción y los mantenimientos programados y no programados para la realización de acciones de mantenimiento preventivo previstos para otras fechas. Este tipo de mantenimiento se emplea con frecuencia en los aerogeneradores, optimizando los costes de logística del mantenimiento y los costes de no producción, ya que es necesario tener las máquinas paradas. En consecuencia, se tendrían en cuenta las previsiones meteorológicas y los mantenimientos correctivos para la optimización de los costes de mantenimiento.

[Besnard et al., 2009] usa un modelo de integración lineal que utiliza las oportunidades para la optimización. El resultado del modelo es una planificación óptima de las tareas de mantenimientos correctivos y preventivos del día teniendo en cuenta las previsiones meteorológicas y las tareas correctivas programadas. El modelo se basa en un modelo propuesto para la industria aeronáutica.

Mediante la Programación Dinámica se pueden resolver los problemas relativos a la toma de decisiones multietapa. En cada momento de decisión, la persona encargada de tomar la decisión observa el estado del sistema y decide asumir una acción basándose en ese estado. Esto tendrá como consecuencia unos costes y una influencia en la evolución del sistema. El objetivo de la Programación Dinámica es minimizar los costes acumulados por la secuencia de decisiones tomadas, descomponiendo problemas mayores en subproblemas, aunque en cada punto en el que se toma la decisión sólo tiene en cuenta el estado actual del sistema. Si lo relacionamos con los sistemas de mantenimiento, significa que las acciones de mantenimiento influyen directamente en el estado del sistema, y no influyen en el deterioro del proceso después de que se completen. En cuanto al tipo de modelos utilizados en el mantenimiento, suelen ser del tipo probabilístico o estocástico, representándose normalmente los fallos funcionales como eventos estocásticos. El problema de la programación dinámica es la complejidad que puede tener, ya que los modelos muy grandes son intratables, y deben utilizarse elementos más simples. Para ello una opción es utilizar una programación dinámica determinista, por lo que se trabaja con estas tres partes: estado y espacio de decisión, funciones dinámicas y de costes y funciones objetivo.

Además, existe la posibilidad de utilizar datos de las diferentes estrategias que se pueden utilizar para cada componente y los costes asociados para definir cuáles pueden ser las mejores actividades que realizar. Este análisis se hace generalmente con un simulador de estrategias de mantenimiento [Conde et al., 2009][Alrabghi & Tiwari, 2013], que introduce los detalles relacionados con los sistemas de predicción (costes de sensores, los gastos de inspección, estimaciones / probabilidad de errores - falsos positivos) con otros datos o información relacionada con los costes de mantenimiento correctivo y preventivo, e información de fiabilidad [Al-Najjar, 2010].

Por ejemplo, [Berdinyazov et al., 2009] presenta un modelo para la simulación de las mejoras en el mantenimiento. Su modelo comienza con la asignación de una de las tres estrategias de mantenimiento (mantenimiento correctivo, mantenimiento periódico, mantenimiento basado en la condición) a cada modo de fallo posible. Entonces se simula el coste asociado a cada modo de fallo y estrategia por medio del análisis de Monte Carlo. Por último, se añade la contribución de todos los modos de fallo para obtener el coste total de mantenimiento.

[Feldman et al., 2009] se centra en el análisis de los costes asociados con el mantenimiento predictivo y con el mantenimiento basado en el pronóstico, comparándolo con el mantenimiento no programado. Realiza una simulación de eventos discretos, implementado como un análisis de Monte Carlo, que se utiliza para comparar diferentes casos de uso con respecto a la línea de base del mantenimiento no programado. En [Asadzadeh & Azadeh, 2014] han tratado la importancia de los aspectos humanos y organizativos en la optimización del mantenimiento basado en la condición.

Por otro lado, en este trabajo de investigación nuestro objetivo es también centrarnos en un problema relacionado con las estrategias de mantenimiento que hasta ahora apenas se aborda en la literatura: el desarrollo de planes de mantenimiento estandarizados relacionados con tareas de mantenimiento preventivo, en escenarios de mantenimiento complejos con flotas de diversas características y recursos de mantenimiento. Estos escenarios aparecen en áreas como los sistemas de transporte de flotas (autobuses, trenes), infraestructuras o ascensores. Aquí, las tareas de mantenimiento preventivo (*Preventive*

Maintenance – PM) deben identificarse y desarrollarse para gestionar el fallo. Las PM son tareas de valor añadido realizadas con la menor mano de obra, tiempo de inactividad y materiales para completar las tareas. El mantenimiento en este tipo de flotas requiere de planes de trabajo estandarizados, y la definición de planes con respecto a las tareas de PM que debe realizar el equipo de mantenimiento es un problema crucial antes de la planificación de recursos. El desarrollo de estos planes no es trivial, ya que las especificaciones de mantenimiento del producto pueden incluir hasta cien acciones diferentes, que se ejecutarán con diferentes frecuencias y con algunas diferencias según las versiones del producto. Por otro lado, no todo el equipo de mantenimiento puede ejecutar todas las acciones (algunas de ellas pueden estar reservadas a expertos) e incluso puede haber diferentes contratos con respecto a la frecuencia de las inspecciones dependiendo del nivel del contrato de servicio o la legislación del país, por nombrar solo algunos ejemplos.

Estas características encajan como un desafío para la toma de decisiones automatizadas a través de modelos de optimización expertos. Las herramientas de toma de decisiones ayudan a los usuarios a mejorar la capacidad de resolver problemas y las capacidades de los sistemas de producción [Medina-Oliva, 2015]. La optimización también está vinculada a la toma de decisiones, minimizando los costes de mantenimiento o el impacto ecológico [Jiang et al., 2018]. En este caso, la estandarización de los planes de mantenimiento no puede resolverse generalmente mediante algoritmos de optimización precisos, que son los que garantizan encontrar una solución óptima; lo que deshabilita la aplicación de algoritmos de optimización precisos a estos problemas es el tiempo de cálculo. Este hecho tiene una consecuencia en la comunidad científica: el nacimiento de las técnicas metaheurísticas. A pesar de no encontrar la solución óptima, estas técnicas aseguran que haya una buena solución con la ventaja de que esta búsqueda podría llevarse a cabo en un tiempo de ejecución razonable. Por lo tanto, dependiendo de las necesidades, puede haber múltiples criterios de optimización simultáneamente. Es posible tener diferentes sistemas de optimización o incluir compromisos para cálculos con criterios parcialmente conectados [Prill et al., 2017].

Los métodos de optimización utilizados para abordar este problema que aparecen en la literatura son variados: algunos de los criterios de optimización están relacionados con el alisamiento de la carga de trabajo de mantenimiento preventivo de la tripulación [Ben-Dava et al., 2009], otros relacionados con el corto plazo [Dedopoulos & Shah, 1995] y programación a largo plazo [Garg, 2006] del trabajo de mantenimiento planificado. La optimización híbrida también se ha utilizado en el mantenimiento para determinar las inspecciones periódicas [Phan & Zhu, 2015]. A diferencia de lo anterior, en este proyecto de tesis nos hemos centrado en optimizar el grupo de tareas que debe realizar el equipo de mantenimiento en una flota, teniendo en cuenta que tener demasiados planes de tareas diferentes podría ser difícil de gestionar por el personal.

4.2 Contribuciones

En este punto se presentan las dos contribuciones relacionadas con la optimización del mantenimiento: un método para la simulación de estrategias y un algoritmo para la optimización de planes de mantenimiento.

4.2.1 Simulación de estrategias de mantenimiento

En este trabajo de investigación presentamos una metodología de simulación que parte de la distribución de densidad de probabilidad de fallo para el equipo o componente mediante la utilización de históricos de fallos. Esta función describe la posibilidad de que un fallo ocurra en un instante de tiempo dado. A partir de dicha función realizamos una serie de planteamientos de simulación con el objetivo de minimizar los costes de mantenimiento.

La metodología para el desarrollo de estrategias está basada en criterios económicos y de fiabilidad. El objetivo final es llegar a una demostración de las mejoras que se pueden obtener mediante las estrategias basadas en condición o predictivas, ya que estas estrategias son teóricamente las más efectivas en cuanto a coste. La mayoría de las veces no se dispone de datos suficientes para una primera aproximación de la mejor estrategia de mantenimiento. Para ello es necesario utilizar este método de simulación que permite aproximar con pocos datos cuál puede ser la mejor estrategia de mantenimiento para un activo o elemento.

Se parte de que se conoce o se puede obtener la distribución de densidad de probabilidad de fallo para el equipo o componente mediante la utilización de históricos de fallos o asemejando los componentes a alguno que existe en la bibliografía. Esta función describe la posibilidad de que un fallo ocurra en un instante de tiempo dado. Se establece típicamente a partir de datos recogidos en ensayos, testeando los elementos y anotando el tiempo en el que ocurre el fallo, o con datos de fiabilidad, por ejemplo, suministrados por el fabricante. En la Figura 29 vemos un ejemplo gráfico de función de densidad y tasa de fallo.

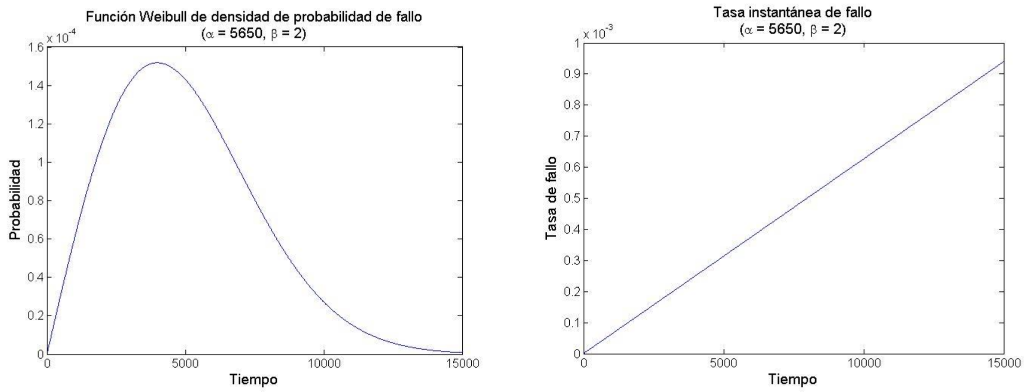

Figura 29. Función de Densidad y de Tasa de Fallo MTTF 5000h y β=2

Conocida esta función es posible aplicar el método de Monte Carlo para realizar un muestreo aleatorio y obtener posibles tiempos de ocurrencia de fallo. Una forma conocida es a partir de la inversa de la función de distribución Weibull acumulada (*F(t)*):

$$t = \alpha \left(\ln \frac{1}{1 - F(t)} \right)^{\frac{1}{\beta}} \quad (8)$$

Donde α es el parámetro de forma y β el parámetro de escala.

Aplicando al valor *F(t)* un muestreo aleatorio para obtener posibles tiempos de ocurrencia de fallo, a medida que el procedimiento se repite, la serie de valores obtenidos ofrece una descripción más fiel a la función Weibull. En la Figura 30 se muestra un histograma para los valores de tiempo generados con un muestreo de tres mil y de treinta mil valores. La función Weibull representada en la figura anterior emplea los mismos valores de α y β. Es importante notar la mejora creciente en el perfil al aumentar el muestreo.

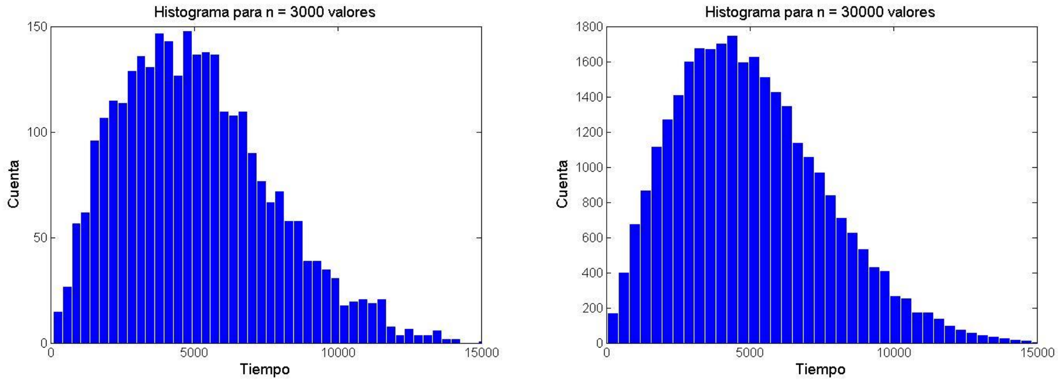

Figura 30. Histograma de valores de tiempo generado con 3000 y 30000 valores

Con el método descrito se obtiene un posible tiempo de ocurrencia de fallo y así, conociendo cuándo este pudiera ocurrir, se puede anticipar el tipo y número de acciones de mantenimiento siguiendo una estrategia determinada y su resultado en términos de coste. Para obtener un resultado representativo es necesario repetir este proceso. Una forma de proceder es contabilizar los tiempos hasta el fallo y los costes en que se incurre hasta que se alcanza un tiempo total estipulado por el usuario. Este tiempo debe ser suficientemente elevado para que el análisis de Monte Carlo ofrezca una buena descripción de la fiabilidad del equipo y para que la estrategia de mantenimiento se desarrolle (por ejemplo, diez veces la vida útil del equipo). Cada vez que se alcanza la vida útil del equipo se añadirá un coste de reemplazo (o de reacondicionamiento si es pertinente) a los costes acumulados.

Adicionalmente, se realiza un número de repeticiones significativo de todo el proceso anterior (digamos, por ejemplo, diez veces), y finalmente, se ofrece como resultado de la estrategia el valor medio del coste por unidad de tiempo.

Comparando el coste por unidad de tiempo obtenido con diferentes estrategias se analiza su coste-efectividad. En la Tabla 15 se muestran los datos generales necesarios para desarrollar el procedimiento descrito.

Tabla 15. Tabla de datos generales

DATO		DESCRIPCIÓN
DATOS GENERALES	Horas de producción	Tiempo total simulado, digamos por ejemplo diez veces la vida útil del equipo o componente
	Vida útil	Vida útil del equipo o componente
	Coste de reemplazo	Coste del reemplazo o reacondicionamiento del equipo o componente al alcanzar el fin de su vida útil
DATOS DE FIABILIDAD	Escala	Parámetros de la distribución Weibull para el equipo o componente. Estos datos deben ser estimados previamente a partir de un histórico de fallos
	Forma	
	Localización	

Las estrategias de mantenimiento consideradas son las siguientes:

- Correctiva: se ejecutan acciones de mantenimiento sólo cuando ocurre un fallo.
- Preventiva: además de acciones correctivas, se ejecutan acciones de mantenimiento de forma sistemática cada cierto intervalo de tiempo predefinido. En el desarrollo de esta estrategia se considera que las acciones de mantenimiento realizadas establecen un nuevo punto de partida en el tiempo para determinar cuándo se realiza el próximo mantenimiento preventivo sistemático. Así, tras una acción correctiva se retrasa el próximo preventivo, como típicamente ocurre con, por ejemplo, los cambios de aceite en máquinas, aprovechando así en lo posible el aceite.
- Predictiva: además de acciones correctivas, se ejecutan acciones de mantenimiento en base a un análisis de detección de fallo del equipo realizado cada cierto intervalo de tiempo predefinido, y con un horizonte temporal de al menos la duración de ese intervalo. El análisis de predicción de fallo

del equipo podría ser realizado por personal de mantenimiento (inspección), un laboratorio (off-line) o tecnología integrada en el propio equipo (on-line).

Desarrollo de la estrategia correctiva

El planteamiento a la hora de simular la aplicación de la estrategia correctiva al mantenimiento del equipo es el siguiente (ver Figura 31):

1. Se aplica el método Monte Carlo y se obtiene un valor de tiempo que se asume que corresponde al tiempo de ocurrencia del próximo fallo del equipo.
2. Este tiempo se suma al tiempo acumulado de uso del equipo, sin superar su vida útil.
3. Si el tiempo acumulado es igual a la vida útil del equipo, se realiza como acción de mantenimiento un reemplazo/reacondicionamiento del mismo, asumiendo que se deja como nuevo e imputando el coste.
4. En caso contrario se realiza una acción de mantenimiento correctivo, también asumiendo que el equipo se deja como nuevo e imputando el coste correspondiente del correctivo.

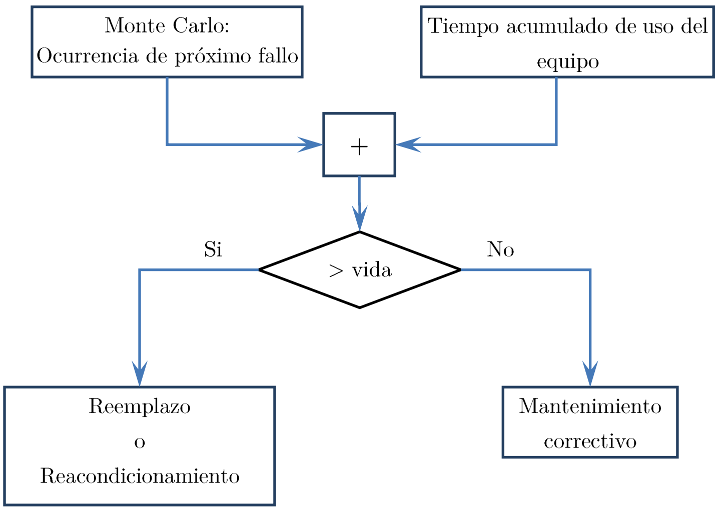

Figura 31. Diagrama de flujo de la estrategia correctiva

Se repite el procedimiento desde el inicio, finalizando cuando se hayan completado las horas de producción y repeticiones estipuladas, y calculando entonces como resultado el coste por unidad de tiempo.

En la Tabla 16 se muestran los datos adicionales necesarios para desarrollar el procedimiento descrito.

Tabla 16. Tabla de datos de estrategias correctivas

DATO		DESCRIPCIÓN
ESTRATEGIA CORRECTIVA	Coste de fallo	Coste en que se incurre al tener que afrontar un fallo inesperado que requiere de un mantenimiento no programado

Desarrollo de la estrategia preventiva

El planteamiento a la hora de simular la aplicación de la estrategia preventiva al mantenimiento del equipo es el siguiente (ver Figura 32):

1. Se aplica el método Monte Carlo y se obtiene un valor de tiempo que se asume corresponde al tiempo de ocurrencia del próximo fallo del equipo.
2. Se suma este tiempo, sin sobrepasar el intervalo de preventivo, al tiempo acumulado de uso del equipo, sin superar su vida útil.
3. Si el tiempo acumulado es igual a la vida útil del equipo se realiza como acción de mantenimiento un reemplazo/reacondicionamiento del mismo, asumiendo que se deja como nuevo e imputando el coste correspondiente.
4. Si, por el contrario, el tiempo registrado es inferior al del intervalo de preventivo, se realiza una acción de mantenimiento preventivo, asumiendo que se deja como nuevo e imputando el coste correspondiente.
5. Si además no se cumplen los puntos 3 y 4, se realiza una acción de mantenimiento correctivo, también asumiendo que el equipo se deja como nuevo e imputando el coste correspondiente.

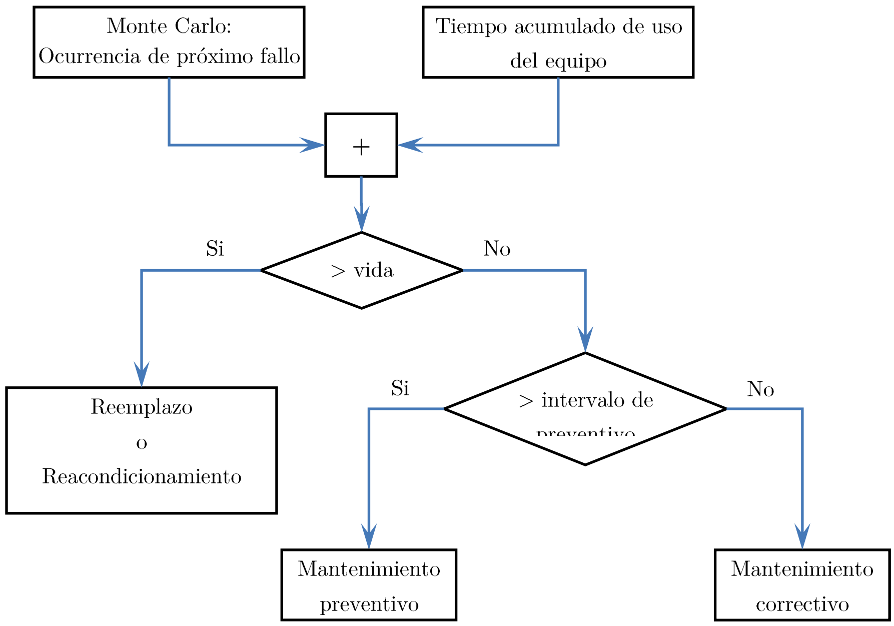

Figura 32. Diagrama de flujo de la estrategia preventiva

Se repite el procedimiento desde el inicio, finalizando cuando se hayan completado las horas de producción y repeticiones estipuladas, y calculando entonces como resultado el coste por unidad de tiempo.

En la Tabla 17 se muestran los datos adicionales necesarios para desarrollar el procedimiento descrito.

Tabla 17. Tabla de datos de estrategias preventivas

DATO		DESCRIPCIÓN
ESTRATEGIA CORRECTIVA	Coste de fallo	Coste en que se incurre al tener que afrontar un fallo inesperado que requiere de un mantenimiento no programado
ESTRATEGIA PREVENTIVA	Coste acción	Coste en que se incurre al llevar a cabo una acción de mantenimiento preventivo sistemático
	Intervalo acción	Intervalo de tiempo prefijado para el mantenimiento preventivo sistemático

Desarrollo de la estrategia predictiva

El planteamiento a la hora de simular la aplicación de la estrategia predictiva al mantenimiento del equipo necesita fijar con antelación la tasa de error del análisis de detección de fallo del equipo. Típicamente esta tasa de error consiste en una probabilidad de falsos positivos y una probabilidad de falsos negativos. La primera responde al caso en que el análisis genera una falsa alarma al indicar que hay un fallo cuando en realidad no es así. La segunda responde al caso contrario, en el que el análisis no indica la presencia de fallo cuando en realidad sí existe. La ocurrencia de falsos positivos/negativos se simula con un análisis de Monte Carlo, realizando un muestreo aleatorio de una distribución uniforme. Si el valor del muestreo es menor que la probabilidad de falso positivo/negativo se señala la ocurrencia de dicho evento.

El planteamiento es el siguiente (ver Figura 33):

1. Se aplica el método Monte Carlo y se obtiene un valor de tiempo que se asume que corresponde al tiempo de ocurrencia del próximo fallo del equipo.
2. Se comprueba si alguno de los análisis de detección hasta el último, antes de fallo o fin de vida útil da lugar a alguna falsa alarma, deteniendo este proceso si esta se produjera y registrando el instante de tiempo en el que ocurre. El coste de los análisis realizados se imputa a los gastos de mantenimiento. Es preciso notar que el último análisis de detección antes de fallo se deja fuera de este proceso porque no hay efecto de falsa alarma.
3. El tiempo registrado (fallo, falsa alarma, o fin de vida útil) se suma al tiempo acumulado de uso del equipo.
4. Si el tiempo acumulado llega a ser igual a la vida útil del equipo se realiza como acción de mantenimiento un reemplazo/reacondicionamiento del mismo, asumiendo que se deja como nuevo e imputando el coste correspondiente a los gastos de mantenimiento preventivo.
5. Si ha ocurrido una falsa alarma, se realiza una acción de mantenimiento de reparación y se imputa el coste correspondiente a los gastos de mantenimiento preventivo. Éstos incluyen también el coste de los análisis de detección realizados como se ha explicado en el segundo punto.

6. Si, por el contrario, se ha llegado al último análisis de detección antes de fallo:

    a) Se comprueba si este da lugar a un falso negativo, en cuyo caso se realiza una acción de mantenimiento correctivo, que se asume deja el equipo como nuevo. El coste de la acción se imputa a los gastos de mantenimiento que, asimismo, incluyen el coste de los análisis de detección realizados como se ha explicado en el segundo punto.

    b) En caso contrario se ha detectado el fallo, y se realiza una acción de mantenimiento de reparación (se asume que justo antes del instante de fallo, aprovechando así al máximo el tiempo productivo. En un caso real el horizonte de predicción puede no ser tan exacto o amplio). El coste de la acción se imputa a los gastos de mantenimiento, que incluyen el coste de los análisis de detección realizados.

    c) Se repite el procedimiento desde el inicio, finalizando cuando se hayan completado las horas de producción y repeticiones estipuladas, y calculando entonces como resultado el coste por unidad de tiempo.

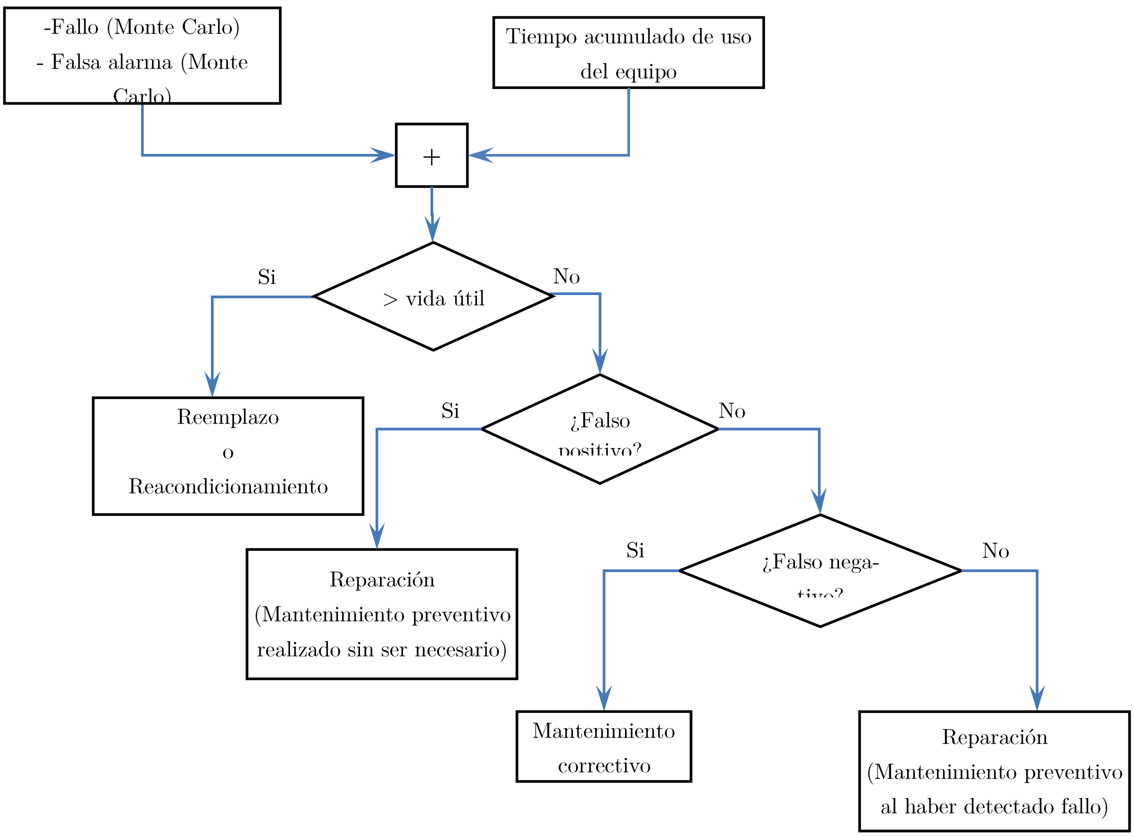

Figura 33. Diagrama de flujo de la estrategia predictiva

En la Tabla 18 se muestran los datos adicionales necesarios para desarrollar el procedimiento descrito.

Tabla 18. Tabla de datos de estrategias predictivas

DATO		DESCRIPCIÓN
ESTRATEGIA CORRECTIVA	Coste de fallo	Coste en que se incurre al tener que afrontar un fallo inesperado que requiere de un mantenimiento no programado
ESTRATEGIA PREDICTIVA	Coste acción	Coste en que se incurre al llevar a cabo un análisis de detección de fallo del equipo
	Intervalo acción	Intervalo de tiempo prefijado para la realización del análisis de detección de fallo del equipo
	Coste reparación	Coste en que se incurre al tener que afrontar un fallo indicado por el análisis de detección de fallo del equipo.
	Probabilidad de falso positivo	Probabilidad de que el análisis de detección de fallo del equipo dé una respuesta errónea, de forma que se genere una falsa alarma al indicar la presencia de fallo cuando en realidad no existe.
	Probabilidad de falso negativo	Probabilidad de que el análisis de condición del equipo falle, de forma que no se indique la presencia de fallo cuando en realidad existe.

El simulador desarrollado se ha comparado con un modelo anterior existente [Berdinyazov et al., 2009]. Este modelo está diseñado como un conjunto de ecuaciones para calcular los costes de mantenimiento utilizando datos similares y una función de fiabilidad con el análisis de Monte Carlo. Sin embargo, el modelo funciona con un número agregado de fallos por periodo (por ejemplo, en un intervalo de mantenimiento preventivo), mientras que el simulador desarrolla la ocurrencia de fallos en el proceso de mantenimiento a medida que se desarrolla el tiempo. Con este mecanismo de simulación podemos introducir condiciones, eventos, decisiones o acciones asociadas con un fallo o entre fallos. Por ejemplo, en el caso de la estrategia de mantenimiento preventivo, el simulador supone que después de realizar las acciones correctivas, el intervalo de tiempo preventivo sistemático debe restablecerse, como suele ser el caso, por ejemplo, con el reemplazo de aceite.

Como se muestra en la Tabla 19, esta situación puede incluirse en el simulador y, en nuestro caso, ofrece ahorros económicos. Además de esto, muestra resultados muy similares entre el simulador y el modelo en estrategias correctivas, de inspección y predictivas, cuando se utilizan los mismos datos. Hay que tener en cuenta que [Berdinyazov, et al. 2009] no considera la posibilidad de tener una probabilidad diferente de falsos positivos y negativos.

Tabla 19. Resultados con método de [Berdinyazov et al., 2009] y el simulador

Estrategia de mantenimiento	*[Berdinyazov, 2009] Coste por unidad de tiempo*	*Simulador Coste por unidad de tiempo*
Correctiva	1,5	1,5
Preventiva	4,7	4,4
Inspección	15,2	15,1
Predictiva	1,5	1,5

También hemos generalizado el concepto de mantenimiento predictivo para incluir sensores en línea, inspecciones y análisis de laboratorio fuera de línea. Además de esto, hemos desarrollado la estrategia combinada preventiva/predictiva para el simulador.

El análisis se ha centrado en tecnologías y procesos con potencial para identificar un fallo antes de que ocurriera, y con la ayuda del conocimiento del equipo de trabajo se encontraron diferentes sistemas para resolver fallos con diferentes grados de confianza y cobertura de los diferentes modos de fallo (por ejemplo, un sensor de partículas caro puede ser mucho más preciso que una inspección periódica del lubricante, pero el grado de rentabilidad varía según el tiempo medio entre fallos (MTBF).

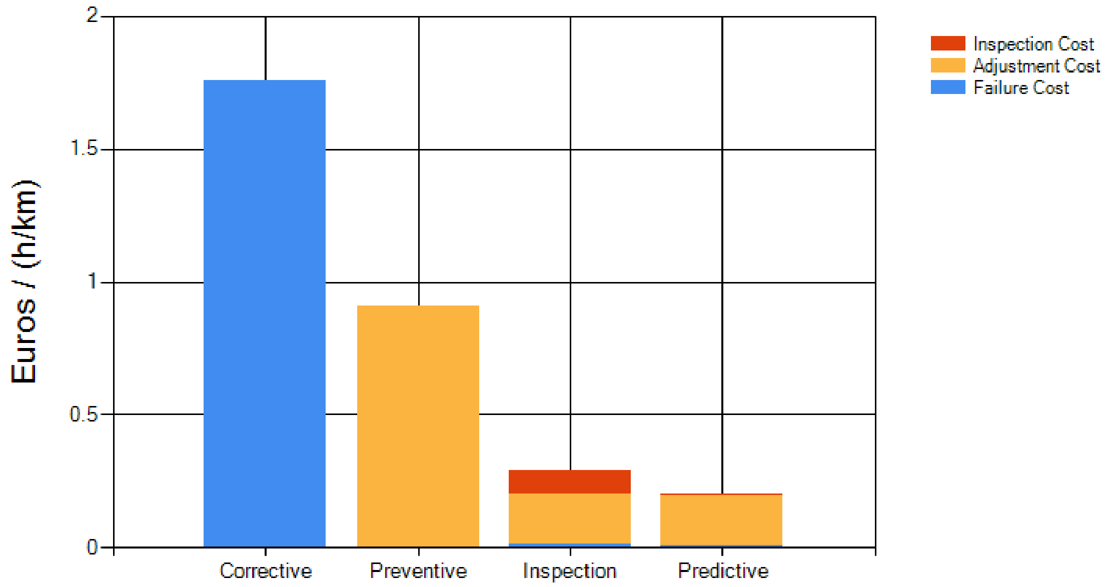

Figura 34. Impacto de las diferentes estrategias de mantenimiento

El análisis termina con la estimación del impacto potencial de las diferentes estrategias (correctivas, basadas en el tiempo, inspecciones) medidas en euros, comparando el coste máximo de las tecnologías seleccionadas y estrategias alternativas, considerando varias variables conocidas o estimadas, como la frecuencia de inspecciones, fiabilidad, coste de fallos, inspecciones y acciones preventivas. Una representación típica se presenta en la Figura 34, donde pueden observarse el coste de las diferentes estrategias de mantenimiento de un componente mecatrónico dentro de un sistema, teniendo en cuenta un coste global segmentado en tres categorías de coste diferentes (coste de reparación y pérdida de ingresos cuando falla el componente; coste de actividades preventivas; y el coste de las actividades de monitoreo, ya sea on-line o remoto).

Estas estimaciones permiten responder diferentes preguntas, como las siguientes:

- ¿Cuál es el objetivo de coste para un sensor si queremos implementar un sistema de monitoreo remoto?
- ¿Qué precisión debe tener el sensor?
- ¿Cuál es la mejor frecuencia de inspección si preferimos esta opción?
- ¿Qué es más rentable: estrategias correctivas o preventivas?

En resumen, este enfoque proporciona un marco para comparar diferentes estrategias y la simulación será realista dependiendo de la información de fiabilidad y costes.

4.2.2 Algoritmo de estandarización de planes de mantenimiento

Este proyecto de tesis presenta un algoritmo para resolver el problema de optimización combinatoria en la definición de planes de mantenimiento preventivo, denominado MOHEDA (*Multi-Objective Hybrid EDA-based algorithm*). Este problema no es fácil de resolver, ya que las tareas realizadas en los activos pueden ser redundantes o no necesarias. El objetivo es una definición más precisa de los planes para reducir los costes de mantenimiento, donde se pueden utilizar diferentes algoritmos de optimización. El nuevo enfoque híbrido con un algoritmo EDA alimentado por el resultado de 4 algoritmos diferentes demuestra que se obtienen mejores resultados que con el uso de los mismos algoritmos de optimización individualmente.

MOHEDA considera los siguientes factores, teniendo en cuenta que se aplica a un conjunto de activos de naturaleza similar:

- Configuración de activos: cada activo tiene un conjunto de tareas para ejecutar dependiendo de su configuración. El concepto de estandarización de un plan no es proporcionar la configuración específica, sino que debe definirse en un nivel superior (por ejemplo, en el caso de los automóviles, podrían ser de gas o diésel, lo que implica diferentes tareas de mantenimiento).

- Tareas y frecuencia: cada tarea tiene una frecuencia mínima que depende de diferentes legislaciones, criterios de seguridad o solicitudes de los clientes.

- Contrato del cliente: el activo pertenece a un cliente, que dependiendo del contrato puede tener ciertas tareas adicionales (por ejemplo, limpieza) o tareas que se hacen con mayor frecuencia.

- Planes: las tareas que se ejecutarán en un activo se agrupan en diferentes planes, debido a sus diferentes requisitos de frecuencia.

- Perfiles de los trabajadores: cada trabajador puede realizar distintas tareas según su conocimiento y experiencia. Se distinguen dos categorías: técnico y especialista.

- Visitas: el mantenimiento de un activo requiere de N planes realizados en V visitas y por una cierta habilidad del operador. Obtener el número de visitas asociadas con cada plan es otro problema de optimización.
- Duración máxima del plan, en minutos (D)
- Parámetro de equilibrio: la diferencia máxima de minutos entre planes (B)

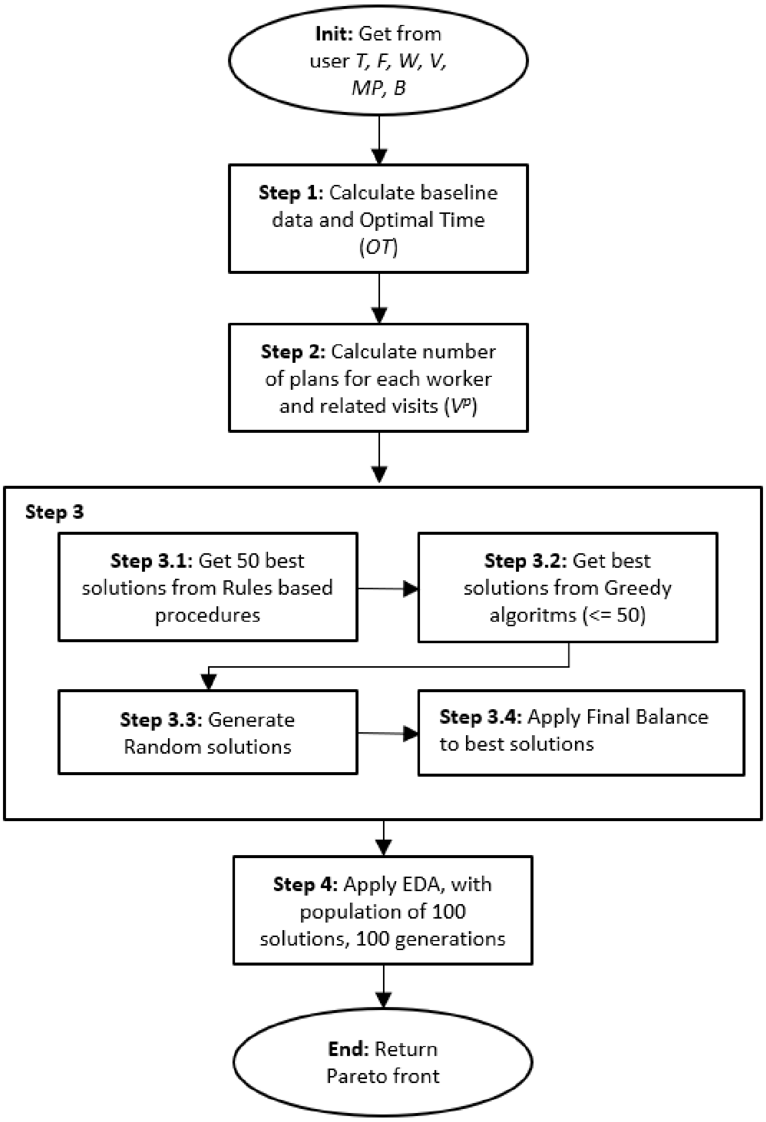

Figura 35. Arquitectura del algoritmo de optimización MOHEDA.

En realidad, el problema de la estandarización de los planes de mantenimiento consiste en resolver 2 problemas de optimización:

- Buscar la mejor combinación entre planes y visitas. Los datos de entrada solo proporcionan el número total de planes y visitas relacionados con el activo. Por ejemplo, los requisitos podrían ser 2 planes en 6 visitas, y el algoritmo debe dar como resultado que el Plan 1 debe realizarse en 2 visitas y el Plan 2 en 4 visitas (o tal vez otra combinación como 1-5 o 3- 3)

- Buscar la mejor estandarización de tareas en los planes / visitas a realizar, de acuerdo con los requisitos de entrada.

La Figura 35 muestra la arquitectura del algoritmo MOHEDA utilizada en la optimización multiobjetivo.

En un primer paso se obtienen los datos de referencia, que consisten en un conjunto de tareas y sus visitas obligatorias para cada una. El tiempo óptimo se define como la suma de las duraciones de estas tareas multiplicadas por sus visitas. Este tiempo óptimo se utiliza para fines de validación.

$$OT = \sum_{i=1}^{i=m} t_i \, v_i \tag{9}$$

donde m es el número total de tareas, t_i es la duración de la tarea y v_i el número mínimo de visitas de t_i.

Obtener el número de visitas asociadas con cada plan es otro problema de optimización. El mantenimiento de un activo requiere de N planes realizados en V visitas y por una cierta habilidad del operador. Esto se calcula mediante otra ejecución de los algoritmos que generan la población inicial (Reglas y Voraces). Sin embargo, esta ejecución se realiza en un pequeño número de iteraciones (<10).

El objetivo del proceso de Planes y Visitas consiste en seleccionar la relación de planes / visitas más adecuada para que la búsqueda sea más limitada y el algoritmo de búsqueda comience desde una configuración definida. El paso de este proceso se inicia con el cálculo de todas las combinaciones posibles de las visitas y los planes por perfiles de operador. Por ejemplo, para un perfil de especialista, 3 planes y 6 visitas (Especialista-3-6), el número de visitas de cada plan podría ser: 1-1-4; 1-2-3; 2-2-2. Para cada combinación posible, se ejecuta el algoritmo híbrido con 10 iteraciones. El mejor resultado obtenido (Por ejemplo 1-2-3), es la configuración utilizada en el siguiente paso.

Este proceso se realiza mediante el algoritmo EDA alimentado por 4 algoritmos de optimización diferentes, obteniendo como resultado el mejor plan proporcionado después de la ejecución de:

1. Procedimiento de reglas minimizando el tiempo.
2. Procedimiento de reglas de equilibrio de planes.
3. Algoritmo voraz que minimiza el tiempo.
4. Algoritmo voraz para maximizar el equilibrio entre planes.

El criterio de evaluación se define como la diferencia entre el tiempo total y el tiempo óptimo calculado en el paso anterior. Al mismo tiempo, se gestionan 2 objetivos diferentes:

- La minimización del tiempo total requerido para realizar el plan en el activo, es decir, la suma de todas las tareas en las visitas, en cada plan.

$$f_1 = min \sum_{i=1}^{i=n} \sum_{j=1}^{j=m} t_j v_i \quad (10)$$

donde n es el número de planes, m el número de tareas relacionadas con el plan i, t_j la duración de la tarea j, y v el número de visitas del plan i.

- La minimización entre las diferencias en la duración de los planes (equilibrio máximo)

$$f_2 = \min\left(\left(\max_i \sum_{j=1}^{j=m} t_j v_i\right) - \left(\min_i \sum_{j=1}^{j=m} t_j v_i\right)\right) \quad (11)$$

Para validar este algoritmo, la experimentación se realizó utilizando la estandarización de planes de mantenimiento de una flota de ascensores, donde se emplearon dos tipos en la flota: eléctricas e hidráulicos. El equipo de mantenimiento se divide en técnicos, que realizan las tareas más básicas, y especialistas, para tareas de mayor complejidad. La ejecución de algoritmos voraces se ha limitado a 1000 iteraciones, y el tiempo de ejecución es inferior a 5 minutos, ya que se requiere de un tiempo de ejecución corto.

La experimentación (Caso #1) comienza desde una situación en la que un técnico especialista ejecuta todas las tareas en 3 planes durante 6 visitas. El tiempo óptimo (OT) es de 148,95 minutos. La ejecución de MOHEDA requiere de 4 minutos para devolver el frente de Pareto usando un PC con Windows 10, Intel Core™ i5 7500 3,4 GHz y 16 Gb de RAM. La Figura 36 presenta el frente de Pareto de MOHEDA con los conjuntos de soluciones óptimas encontradas. La Tabla 20 proporciona las 2 soluciones óptimas encontradas de acuerdo con las funciones objetivo F_1 (minimizar el tiempo total) y F_2 (minimizar el desequilibrio). Estas 2 soluciones óptimas presentan diferencias significativas: F_1 proporciona 3 planes diferentes que coinciden con el tiempo total y el tiempo óptimo. Esto implica un desequilibrio de 21,12 minutos entre los diferentes planes. Este hecho se debe a que el primer plan tiene una duración significativamente más corta que los restantes. Sin embargo, F_2 proporciona una solución equilibrada perfecta, pero 62,51 de tiempo extra por año en relación con la solución F_1. En realidad, el uso de la solución F_2 implica un aumento del 41% en el tiempo de mantenimiento en comparación con la solución F_1, por lo tanto, un incremento similar en el coste de mantenimiento. Por esta razón, la empresa de mantenimiento de ascensores debería considerar una solución intermedia del frente de Pareto que proporciona MOHEDA, siendo posible traducir los resultados a una estimación del coste de mantenimiento. Este aumento en el coste con respecto a la solución F_1 permite ahorrar dinero en el aprendizaje, reducir los errores humanos causados por tener planes demasiado diferentes y simplificar la planificación de mantenimiento para el equilibrio de carga del personal de mantenimiento.

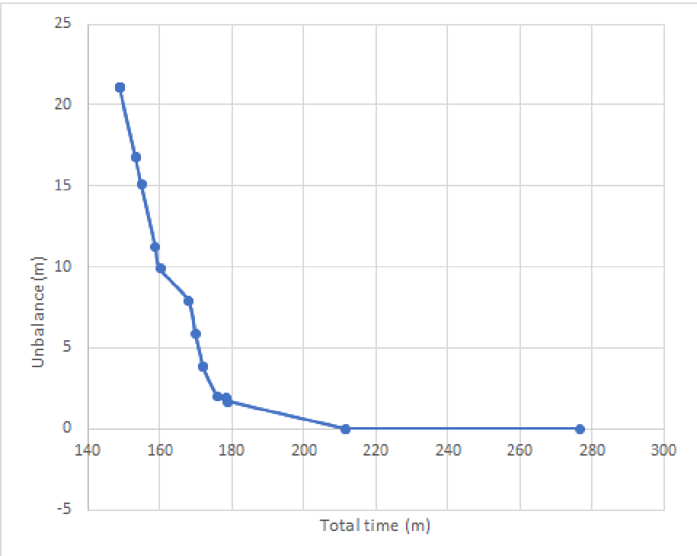

Figura 36. Frente de Pareto de Caso #1

Tabla 20. Extremos del frente de Pareto en Caso #1

Objectivo ($\boldsymbol{F_x}$)	$\boldsymbol{P_1}$ Sp V_1=4	$\boldsymbol{P_2}$ Sp V_2=1	$\boldsymbol{P_3}$ Sp V_3=1	**Tiempo Total (*TT*)**	**Diferencia**	**Desequilibrio**
F_1	17,49	38,91	38,90	148,95	0	21,12
F_2	35,25	35,24	35,24	211,46	+62,51	0,01

MOHEDA también muestra cómo el uso de diferentes perfiles de personal de mantenimiento permite una mejora significativa en los tiempos y costes de mantenimiento. El Caso #2 considera la situación en la que el Especialista ejecuta el mantenimiento todos los meses durante un año, estableciendo solo 2 planes diferentes. En un mantenimiento anual, el primer plan se ejecuta cada 6 meses y el segundo el resto de los meses. OT es igual 380,40 minutos. Los resultados iniciales se muestran en la Tabla 21. Considerando el objetivo principal de minimizar el tiempo, los resultados indican un exceso de 13,33 minutos como mínimo.

Tabla 21. Extremos del frente de Pareto en Caso #2

Objectivo (F_x)	$\boldsymbol{P_1}$ Sp V_1=10	$\boldsymbol{P_2}$ Sp V_2=2	**Tiempo Total (TT)**	**Diferencia**	**Desequilibrio**
F_1	28,20	55,87	393,73	+13,33	27,67
F_2	41,79	42,58	530,03	+149,63	0,79

Teniendo en cuenta esto, el objetivo principal es ahorrar dinero utilizando dos perfiles de personal de mantenimiento diferentes (Especialista y Técnico). Partiendo de este caso, el Caso #3 define un especialista que ejecuta 2 planes cada 6 meses y un técnico que ejecuta 1 plan en 10 visitas. La Tabla 22 muestra cómo el especialista mejora el tiempo mientras mantiene la duración de las tareas básicas, relacionadas con la situación anterior en la Tabla 21.

Este resultado significa una mejora significativa de 13 minutos por ascensor. Suponiendo una flota de ascensores de 100 unidades y considerando que el coste por hora del técnico es un 40% menor que el uso de un especialista, el ahorro es cercano al 32% en este caso de uso.

Tabla 22. Extremos del frente de Pareto en Caso #3

Objectiveo (F_x)	P_1 Sp V_1=1	P_2 Sp V_2=1	P_3 Tc V_3=10	Tiempo Total (TT)	Diferencia	Desequilibrio
F_1	49,21	49,20	28,20	380,40	0	0,01
F_2	45,25	45,25	36,15	451,97	+71,57	0

4.3 Conclusiones y trabajo futuro

En este trabajo de investigación se ha presentado una metodología de selección de estrategias de mantenimiento, que parte de la distribución de densidad de probabilidad de fallo para el equipo o componente mediante la utilización de históricos de fallos. Esta función describe la posibilidad de que un fallo ocurra en un instante de tiempo dado. A partir de dicha función se realizan una serie de planteamientos de simulación con el objetivo de minimizar los costes de mantenimiento. La metodología para el desarrollo de estrategias está basada en criterios económicos y de fiabilidad. El objetivo final es llegar a una demostración de las mejoras que se pueden obtener mediante las políticas basadas en condición o predictivas, ya que dichas políticas son teóricamente las más efectivas en cuanto a coste.

Por otro lado, en un problema de optimización, tomar un solo algoritmo podría encontrar una solución óptima dependiendo del caso específico utilizado, pero un algoritmo único no encuentra resultados fiables de manera genérica. Este trabajo de investigación presenta un nuevo algoritmo para resolver el problema de optimización combinatoria en la estandarización de los planes de mantenimiento, utilizando un enfoque híbrido con 4 algoritmos diferentes. El uso de este algoritmo permite reducir costes o permitir una planificación posterior más fácil. y es además completamente escalable en número de tareas, planes, visitas y perfiles de operador. Las combinaciones híbridas se han implementado en un proceso de varias etapas. Sin embargo, después de este trabajo, consideramos que es posible aprovechar la combinación de algoritmos de otras maneras, siendo de interés en un futuro mejorarlo, expandiendo tanto las tipologías de optimización como la forma de combinar sus resultados.

4.4 Publicaciones

Revistas y libros

Gilabert, E., Fernandez, S., Arnaiz, A., & Konde, E. (2015). Simulation of predictive maintenance strategies for cost-effectiveness analysis. Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture, 231(13), 2242-2250. (JCR Q3)

Gilabert E., Konde E., Arnaiz A., Sierra B. (2020). A multi-objective hybrid EDA-based algorithm for optimizing preventive maintenance plans. Reliability Engineering & System Safety. Submitted in Revision process. (JCR Q1)

Contribuciones a congresos

Gilabert, E., Konde, E., Fernandez, S., Revilla, O. (2010, May) Condition Based Maintenance for Sustainability. M. Garetti, D. Centrone (Eds.) Proc of the 2nd Workshop Maintenance for Sustainable Manufacturing. Euromaintenance. Verona (Italy). Pp 19-23.

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5 Contribuciones principales

En esta sección se describen las principales contribuciones de este proyecto de tesis. La mayoría de estas contribuciones han sido presentadas en revistas y conferencias, que se pueden consultar en el capítulo 1.8 de este documento.

5.1 Servicios web Inteligentes en e-mantenimiento

Desarrollo de una plataforma capaz de proporcionar servicios web de mantenimiento avanzado, llamada DYNAWeb. Se trata de una plataforma de información y comunicación que proporciona interacción operativa entre tecnologías *plug-in* en el marco de un escenario de información distribuida, donde las tecnologías de interés pueden variar de un caso de uso de mantenimiento a otro. Se ha definido los actores asociados a las actividades de DYNAWeb, donde se identifica el papel principal, los datos esperados y su participación en los pasos de procesamiento de información en capas de OSA-CBM. Los actores están enmarcados en una arquitectura flexible con respecto a los canales de comunicación.

5.2 Modelo de datos para e-mantenimiento e interoperabilidad

Definición un modelo de datos para la gestión y el mantenimiento de la configuración, teniendo en cuenta todo el ciclo de vida de los activos. La gestión de la configuración conduce a un mantenimiento más efectivo y hace posible tener una mejor trazabilidad del equipo, teniendo en cuenta todos los cambios que tiene, mejorando la logística de mantenimiento conociendo la configuración real de un activo, y comparando entre la configuración de dos máquinas para seleccionar la mejor para la empresa. El modelo de datos empleado respalda la gestión, pero además ha sido definido de manera amplia, teniendo en cuenta aspectos relacionados con la ejecución del mantenimiento, la logística, los costes, el estado y la fiabilidad, así como la identificación y el control de la configuración.

5.3 Red Bayesiana para diagnóstico por vibraciones

Desarrollo de una Red Bayesiana de diagnóstico para máquina herramienta basándose en la información del espectro de vibraciones. La Red Bayesiana fue integrada en TESSnet, que es una plataforma web que se puede usar como Sistema de Gestión de Mantenimiento Predictivo (PMMS). Este trabajo de investigación expone las necesidades que surgen dentro de la aplicación de sistemas inteligentes para el mantenimiento de activos industriales. Estos problemas han permitido identificar procesos de aprendizaje que pueden ser necesarios para complementar y apoyar los procesos inferenciales. El despliegue completo y las pruebas de las capacidades de aprendizaje se realizan con la herramienta HUGIN, que incluye los algoritmos necesarios para implementar el sistema de aprendizaje. Existe la necesidad de desarrollar sistemas adaptativos que puedan mejorar el soporte de software para decisiones de mantenimiento en muchos campos de aplicación además de máquinas herramienta y elevadores. Esta contribución es una buena alternativa para proporcionar los mecanismos de adaptación necesarios.

5.4 Metodología de AMFE a Red Bayesiana

La principal contribución se basa en una metodología que automatiza la generación de modelos de diagnóstico. Para ello se apoya en la combinación de las características y propiedades de un Análisis de Modos de Fallos y Efectos (AMFE), que recogen la información de fallos de una forma estructurada, y de las Redes Bayesianas, que permiten la generación del modelo de diagnóstico con incertidumbre y aprendizaje. A partir de ellos definimos hemos una metodología para la creación de un sistema de diagnóstico, la cual se ha aplicado en motores diésel de buques marinos de carga. En este proyecto de tesis se ha descrito además un mecanismo para resolver la falta de información de probabilidades.

5.5 Simulación de estrategias de mantenimiento

Esta contribución consiste en una metodología de simulación que parte de la distribución de densidad de probabilidad de fallo para el equipo o componente mediante la utilización de históricos de fallos. Esta función describe la posibilidad de que un fallo ocurra en un instante de tiempo dado. A partir de dicha función se realizan una serie de planteamientos de simulación con el objetivo de minimizar los costes de mantenimiento. La metodología para el desarrollo de estrategias está basada en criterios económicos y de fiabilidad. El objetivo final es llegar a una demostración de las mejoras que se pueden obtener mediante las estrategias basadas en condición o predictivas, ya que estas estrategias son teóricamente las más efectivas en cuanto a coste.

5.6 Algoritmo de estandarización de planes de mantenimiento

Esta contribución consiste en un nuevo algoritmo multiobjetivo (MOHEDA) para resolver el problema de optimización combinatoria en la estandarización de los planes de mantenimiento, utilizando un enfoque híbrido con 4 algoritmos diferentes combinados con el algoritmo evolutivo EDA. El uso de este algoritmo permite reducir costes o permitir una planificación posterior más fácil. y es además completamente escalable en número de tareas, planes, visitas y perfiles de operador.

6 Conclusiones

El trabajo realizado anticipa diferentes escenarios y áreas de investigación muy actuales, pero menos conocidos o prácticamente inéditos al comenzar estos trabajos. En primer lugar, la actividad de este proyecto de tesis se alinea con el notable auge que la aplicación de tecnologías de Inteligencia Artificial (IA) tiene en los últimos años. En concreto, la aplicación de tecnologías IA son la base de dos de las tres áreas de desarrollo de este trabajo de investigación, y en ambas áreas la IA va más allá del concepto *machine learning* de aprendizaje y modelado basado en datos, sino que busca, tanto en el diagnóstico como en la optimización, modelos y algoritmos que integren no sólo un aprendizaje basado en los datos existentes sino también conocimiento experto, como es el uso de Redes Bayesianas en diagnóstico o la hibridación de modelos heurísticos y genéticos en optimización (Ver Figura 37).

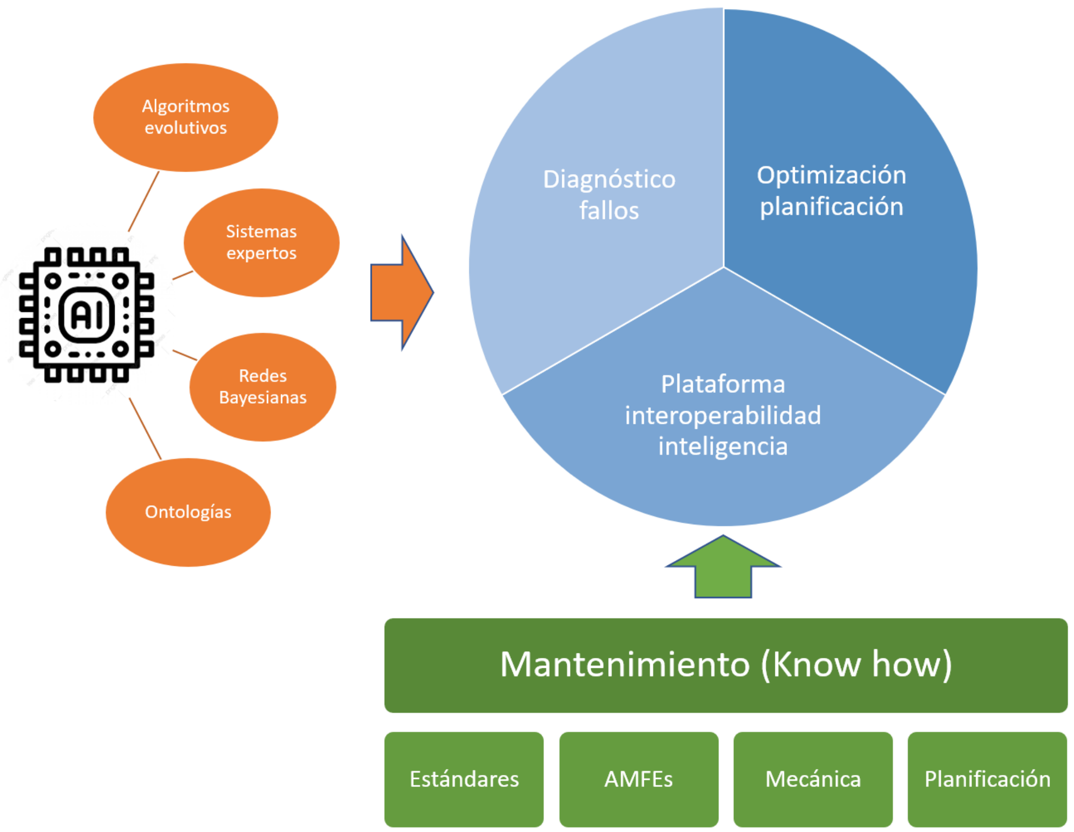

Figura 37. Áreas de investigación en este Proyecto de Tesis

En una línea de razonamiento parecida, el objetivo y las acciones realizadas en este trabajo están en consonancia con el concepto de *Data Science* [Loukides, 2011], [Provost & Fawcett, 2013] en donde existen 3 áreas de desarrollo para lograr una buena orientación hacia la ciencia de los datos: Por un lado, es necesario trabajar los conocimientos estadísticos y matemáticos presentes, por ejemplo, en las tecnologías de optimización y diagnóstico mostradas en los capítulos 3 y 0. Además, es necesario trabajar las plataformas de datos que permitan explotar las tecnologías anteriores, como se ha realizado en el capítulo 0. Finalmente, este trabajo de investigación está enlazado a un dominio (el de mantenimiento, y más en concreto el mantenimiento basado en condición) sustentado en el conocimiento existente en Tekniker, que el autor ha adquirido durante su formación y trabajo en los diferentes proyectos mencionados en la sección 1.7.

Finalmente, el concepto de e-mantenimiento trabajado en el capítulo 0 se orienta al desarrollo de métodos de interoperabilidad y conectividad de datos relacionados con la gestión de activos, y es un precursor de diferentes trabajos en torno al concepto de Internet de las Cosas (*Internet of Things* – IoT), como se indica en [Kinnunen et al., 2016], o en [Tavallaeli & Scharlak, 2018] en donde el desarrollo de servicios de estándares abiertos y la utilización de tecnologías semánticas se integra con otros sistemas de gestión de datos [Schoning et al., 2020]

6.1 Trabajo futuro

Aunque existen muchos avances en la aplicación de tecnologías de IA para la mejora de las estrategias y procesos de mantenimiento, existen todavía muchos retos, tanto en el nivel de uso y aplicación de estrategias avanzadas, como en nuevas estrategias y aplicación de tecnologías.

En primer lugar, desde un punto de vista de aplicación, hay que destacar el incremento en la búsqueda de estrategias de mantenimiento que van más allá del mantenimiento predictivo, en donde se destacan sobre todo dos conceptos: el mantenimiento prescriptivo, ya desarrollado en este trabajo, relacionado sobre todo sobre una mejor planificación de acciones al conocer no sólo la evolución de la salud de un activo sino el impacto de las diferentes decisiones de mantenimiento; y el concepto de mantenimiento proactivo, relacionado en este caso con la eliminación de causas raíces de fallo y por tanto con la extensión de la vida de los activos [Jantunen et al., 2019]. Es destacable que ambos conceptos hacen referencia a su aplicación en entornos de sistemas ciber-físicos de producción (*Cyber Physical Production System* – CPPS) [Hegedüs et al., 2018], [Ansari et al., 2019] en donde la viabilidad y el éxito de ambas aproximaciones se apoya tanto en la existencia de los datos tanto de mantenimiento como de operación, y en la capacidad de las tecnologías existentes para procesarlos de forma dinámica e inteligente.

Por otro lado, desde el punto de vista de la mejora en las tecnológicas, destaca la importancia creciente de los conceptos de 'confianza' y colaboración entre los sistemas inteligentes y las personas. Esta es una demanda global, que en Europa se articula a partir de la iniciativa *"Ethics guidelines for trustworthy AI"*[4], y que enlaza con ámbito de la una extensión de este trabajo se puede enfocar en una mayor explicabilidad de las decisiones o recomendaciones que realizan los sistemas inteligentes, y en una mayor interacción o colaboración con los operadores (*Human in the loop*) para mejorar la toma de decisiones. Por ejemplo, en procesos enlazados a espacios de soluciones complejos (como la optimización conjunta de O&M de diversos sistemas en una misma planta, teniendo también en cuenta criterios de minimización de stocks, logística, etc.) la posibilidad de una interacción fluida con los operadores ayudará por ejemplo a afinar la identificación de las funciones objetivo y/o a evaluar si es conveniente o no proseguir una búsqueda o admitir el mejor resultado encontrado.

La explicabilidad de las decisiones es también básica para poder proporcionar esa mayor confianza y colaboración. Los algoritmos realizados en este trabajo se apoyan en modelos que presentan una cierta 'transparencia' en sus posibilidades auto-explicativas tanto en los algoritmos de optimización (mezcla de reglas heurísticas con algoritmos evolutivos) como en el de los sistemas de diagnóstico (Redes Bayesianas) realizados en este trabajo. Esto implica que no es necesario desarrollar una algoritmia asociada de complejidad, pero si es necesario tener capacidad de descomponer el modelo en sus partes constituyentes, y/o replicar el aprendizaje que se haya realizado, tal y como indica [Arrieta et al., 2019] (Ver Figura 38).

Finalmente, se espera una mayor implicación de las tecnologías semánticas en el diseño y desarrollo de modelos fundamentados en experiencia y conocimiento, tanto en la parte de diagnóstico y predicción, como en la parte de optimización.

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https://ec.europa.eu/digital-single-market/en/high-level-expertgroup-artificial-intelligence

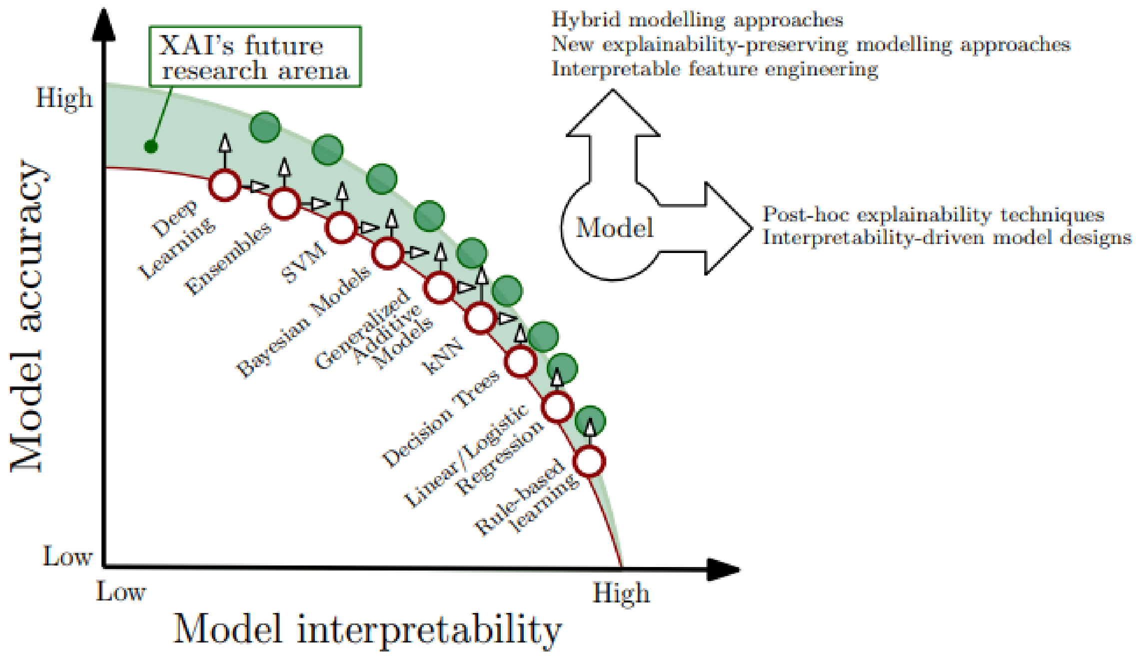

Figura 38. Compromiso entre complejidad e interpretabilidad de modelos de IA [Arrieta et al., 2019]

Mas allá del trabajo realizado hasta ahora que ha servido para dar soporte para una mejor interoperabilidad entre sistemas, el desarrollo actual de estas tecnologías puede servir tanto para mejorar la explicabilidad o la colaboración con los operadores de mantenimiento [Emmanoulidis et al., 2019], como para mejorar el diseño y desarrollo de los modelos mismos: la estructura y las reglas que gobiernan las recomendaciones, incluyendo la posible generación de 'gemelos digitales' del proceso o activo, como en [Banerjee et al., 2017]. En esta dirección es preciso tener en cuenta tanto la necesidad de 'formalizar' las ontologías que se desarrollan y enlazarlas con ontologías ya existentes y más genéricas, como propone [Karray et al., 2019] como la existencia de herramientas como los grafos de conocimiento, que pueden simplificar el dialogo entre los modelos semánticos desarrollados y un operador [Grangel-González et al., 2018]

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Parte II
Publicaciones

8 Publicaciones

8.1 Simulation of predictive maintenance strategies for cost-effectiveness analysis

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Resumen

Este artículo presenta una metodología que proporciona una evaluación continua de las tecnologías de mantenimiento predictivo con respecto a escenarios empresariales específicos. La metodología integra técnicas y estándares de análisis de fiabilidad y mantenimiento existentes. También se agrega un paso crítico de simulación donde se simulan diferentes estrategias de mantenimiento predictivo para obtener la estrategia de mantenimiento óptima. Esta simulación de Monte Carlo se basa en la información de fiabilidad basada en la distribución de probabilidad de fallo del sistema o componente, proporcionando como resultado la estrategia óptima entre las opciones propuestas. El artículo finalmente explica cómo esta metodología tiene un impacto positivo no solo en la rentabilidad de los procesos de mantenimiento, sino también en la información de mantenimiento disponible.

Simulation of predictive maintenance strategies for cost-effectiveness analysis

Eduardo Gilabert, Santiago Fernandez, Aitor Arnaiz and Egoitz Konde

Abstract

This paper presents a methodology that provides a continuous assessment of predictive maintenance (PdM) technologies with respect to specific business scenarios. The methodology integrates existing reliability and maintenance business analysis techniques and standards. The positive impacts that may have the implementation of these technologies have always been in mind. A critical simulation step is also added where different PdM strategies are simulated in order to obtain the optimal maintenance strategy. This Monte Carlo simulation relies on the reliability information based on the probability density distribution of failure for the system or component, providing as a results de optimal strategy among proposed options. The paper finally explains how this methodology has a positive impact not only on the cost-effectiveness of maintenance processes, but also on the maintenance information available.

Keywords
Predictive maintenance, Monte Carlo simulation, cost-effectiveness, maintenance strategies

1. Introduction

Performance improvements in the maintenance and conservation activities of physical assets are measured by availability and operational reliability. They should be obtained preserving maximum quality and safety levels and minimizing the costs. In the current scenario of competitiveness, improvement efforts are essential to reach high levels of effectiveness and efficiency in every company's production or operational department. The purpose is to achieve competitive advantage (in products or offered services) based on different hard-to-copy aspects, i.e. know-how.

To obtain maximum performance, the organizations must be prepared for changes and there are three interconnected areas in the change concept [1]:

- Processes, work fluxes to achieve the improvements (e.g. doing more preventive work instead of corrective work, etc.).
- Technologies to facilitate or enable some processes.
- Organization and people within the organization must validate any change, so there is a need of tools to ease changes.

One of the approaches for improvement is to identify and to apply predictive maintenance (PdM) techniques and tactics which would help to identify anomalies with high reliability. In this context, PdM is still an important area of improvement for Original Equipment Manufacturers (OEMs), maximizing the value of their products through extended lifetime services, not just within warranty periods, as well as for end users – maximizing the availability and performance of their assets with optimum maintenance costs.

Usual PdM systems are mostly centred in just *condition monitoring*. That is, the identification of anomalies in order to mitigate critical system failures before time-based replacement (or repair) is completed. A typical feature is modelling the degradation process, using the condition monitoring data to estimate de remaining useful life and the making maintenance decisions [1]. This is the usual approach at systems that require extra safety approaches (e.g. nuclear, aerospace). However, PdM true potential is related to the extension (or cancellation) of repair and replacement periods, helping companies in their shift from 'fail and fix' policies to 'predict and prevent' [3].

There are different ways to achieve cost-effective PdM for physical assets. One vector of improvement is the use of high-tech elements can serve to help maintenance specialists in rapid on-site inspections, or even to perform an on-line remote assessment of the asset conditions. Another vector is to rely on third party services that can perform specialized analysis, diagnostics and audits over specific areas (e.g. the lubrication process).

1.1. The maintenance information gap

The positive effect of PdM approaches in the improvement of operation and maintenance processes may be mitigated by different reasons. The lack of adequate information concerning the maintenance process is one of them. Lack of information can be due to different causes. Several examples follow:

- The signal is acquired (e.g. vibrations) but stored just locally due to difficulties/cost in data transmission (e.g. wind turbines).

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- Usually the failures and work order handled by maintenance personnel does not feed the OEM in order to understand the machinery reliability – Different departments and even different companies.
- Lack of information transmission between operation and maintenance processes, apart from scheduled plans for preventive maintenance and inspection. No information on machinery performance, nor on short/medium term operational schedule.
- Condition signal acquired by third party services (e.g. vibration, lubrication, thermography) and handled in isolation, with a single 'condition monitoring' purpose.

At the end there is a lack of proper acquisition, transmission and storage of vital data that needs to be shared and communicated with the appropriate areas of the company (management, operation, maintenance, OEM). It may be argued that this lack of the information systems is because of the organizational culture and of the business processes. However, in many cases it may be happening the opposite: The lack of adequate information channels is motivating a certain culture of isolation.

This is critical and has at minimum two different effects on the development of any strategy for continuous improvement:

- At the starting point for any improvement, the quantity and quality of information that optimization of maintenance strategies may need can be discouraging. Simulation tools can help identifying how a new PdM approach may help - or hinder- in the cost-benefit of the life cycle of the product or global productivity of the plant. But most of them rely on several types of data not available at the beginning.
- During the whole process, there is a need for metrics. The identification of true improvements is also difficult if only partial information is available. The Key performance Indicators (KPIs) initially planned can become unreachable.

1.2. Existing approaches to Cost-effectiveness analysis

In maintenance, various methodological frameworks and models deal with the identification, comparison and improvement in maintenance policies. For example, [4] studies the criteria for comparing maintenance approach and it proposes an evaluation methodology for identifying the most informative by means of fuzzy multiple criteria decision making. Marquez et al [5] defined a process for maintenance management classifying maintenance engineering techniques, introducing a methodological framework in eight steps.

The importance of a cost-effectiveness analysis is key because it is the way to indicate if any profit or competitive advantage can be achieved by using more automatic maintenance tasks, especially predictive maintenance.

This analysis is usually done with a maintenance strategies simulator [6,7], which introduces the details related to predictive systems (sensor costs, inspection costs, estimations/probability of errors –false positives) with other data or information related to corrective and preventive maintenance costs and reliability information [8].

For instance, Berdinyazov et al. [9] presented a model for simulating improvements in maintenance. Their model begins with assigning each possible failure mode to one of three maintenance policies (i.e. corrective maintenance, periodic maintenance, condition-based maintenance). Then it simulates the cost associated with each failure mode and policy by means of Monte Carlo analysis. And finally, the contribution of all failure modes are added for obtaining the total maintenance cost.

Exakt is a software package by Optimal Maintenance Decisions Inc. for predicting and optimizing condition-based maintenance in order to improve reliability, reduce failures and save maintenance costs. It works by correlating measurable condition variables with failure modes and, as such, requires inputs such as event and condition data.

In [10], Feldman et al. focuses on an analysis of the costs associated with predictive, prognostic maintenance as compared to unscheduled maintenance. Discrete event simulation, implemented as a Monte Carlo analysis, is used for comparing various use cases with respect to the baseline unscheduled maintenance. In [13], Asadzadeh and Azadeh have dealt with the importance of human and organizational aspects in optimization of condition-based maintenance.

In [11] Wang uses bearing vibration to estimate the component condition and residual life. On top of the estimation of the component's life, costs are added in order to support decision process on the optimal replacement time. In [12] Xiang et al. modelled equipment deterioration with time to failure distributions. Weibull distribution is fitted to the time of first failure data. For estimating the Weibull distribution, instead of actual data, a simulation of an environment is performed with a Markov chain in order to generate the data. Cost-benefit of condition-based maintenance policy is assessed via simulation including corrective, preventive and periodic inspection actions, or in other words, including both age-based and condition-based maintenance policies.

1.3. Scope and contents of the paper

This paper illustrates a methodology to overcome this information gap, which helps in starting to take decisions with little information, and allows a progressive increase in confidence (from a statistical point of view as well concerning communication with management) which depends on the level of information collected.

Section 2 explain the overall methodology for constantly improving maintenance activity focusing on reducing maintenance costs, in order to achieve a optimal maintenance strategy, mainly based on predictive technologies.

Finally, section 3 concentrates on the core of improvement model, presenting an implementation of a maintenance strategy simulation based on the probability density distribution of failure for the selected system or component.

2. Improvement model

Maintenance should be a constantly improving activity, which enhances the quality of service and optimizes operating costs.

Condition-based maintenance and predictive strategies based on cutting-edge technologies are arriving on the market and their continuous cost reduction opens wide opportunities, helping the operation and maintenance personnel to perform tasks more effectively.

There are cost-effectiveness studies of the different types of strategies but it is normally difficult to measure with these tools the impact of predictive strategies [9,10,11,12,14,15,16]. To overcome this gap, a simple model was developed to solve the difficulty of showing how predictive maintenance could help in a cost-effective way. This model is based on the application of different existing tools (Balance Scorecard, Failure Modes Effects and Cause Analysis - FMECA, Preliminary Hazard Analysis - PHA,…), and it follows a six-step structure based on a Deming cycle to gradually improve each process or service adapted to maintenance needs.

The innovation of this improvement model compared to previous approaches is the generalized concept of predictive maintenance to include, besides on-line sensors, inspections and off-line laboratory analysis. Besides this, we have additionally developed the possible combination of strategies for the simulator. Furthermore this simulator considers the possibility of having different probability for false positives and negatives as it works with accuracy.

The cycle is continuously fed with new information to achieve an optimal maintenance working way in a cost-effective manner and keeping in mind strategies that are based on predictive technologies. The steps are carried out in a cyclical manner as shown in next figure.

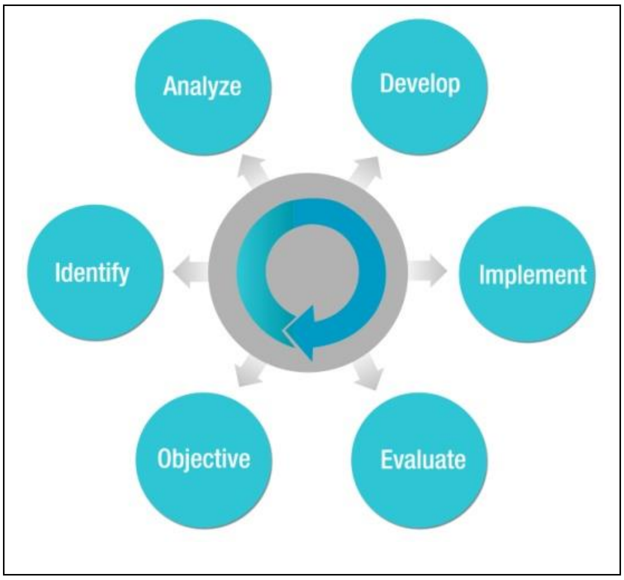

Figure 1. .

2.1. Selection of the objectives (step 1)

The first step is to establish the main objective. It is essential to know exactly the situation of the company in order to know what should be improved and to align the vision-mission-strategies-objectives-indicators. These objectives should be identified with KPIs with different approaches: financial, learning or technical. There are many different techniques that can serve to achieve the correct alignment between the company and indicators, such as Balanced Scorecard.

2.2. Identification of the most important products/processes (step 2)

The next step is the identification of the main objects or processes where the improvements are going to be critical with respect to their impact on the selected KPIs. Results include machinery parts (e.g. planetary systems), product types (e.g. specific wind turbine gearboxes) or target sectors (e.g. wind-farms with less than 50 MW) among others.

Criticality tables are used in order to rank the results and select an appropriate subset for further analysis and simulation in the next steps.

2.3. Analysis of selected product/processes (step 3)

An exhaustive analysis of selected products/processes is carried out to have a clear idea of their main important aspects. Analyzing the most critical assets is very useful in order to obtain the selected objectives.

The information of different tools: from Failure Mode and Effect Analysis (FMEA) to Risk Analysis (PHA) among others. A complete understanding of the assets identified in the previous step gives a better way to make improvements.

2.4. Identification of optimized asset management strategies for each critical product/ processes (step 4)

This step consists of an analysis and an assessment of various maintenance strategies for the selected critical products/ processes. There are a number of different techniques for implementing and analyzing these aspects.

The cost assessment simulation is done in this step and is the most critical part of the whole model. An ad-hoc optimization tool has been developed to better simulate the cost-effectiveness, and therefore this step will be further explained in this article.

The key issues in the simulation process are to use a valid source of information, to employ a relevant selection of key characteristics and behaviours, make approximations and assumptions when necessary and understand the fidelity and validity of the simulation outcomes. The simulation is developed by means of a Monte Carlo approach where probability density distribution of failure for the equipment or component is estimated, firstly from bibliographical data and later from real failure information, increasing progressively the confidence value.

2.5. Implementation and assessment (Steps 5 & 6)

These steps are run iteratively, in a separate cycle, in order to compare the simulation results in step 4 with the real results obtained after the deployment of the new strategies. This deployment is normally progressive (concept complete design, lab trials, first installs on selected machines, etc.).

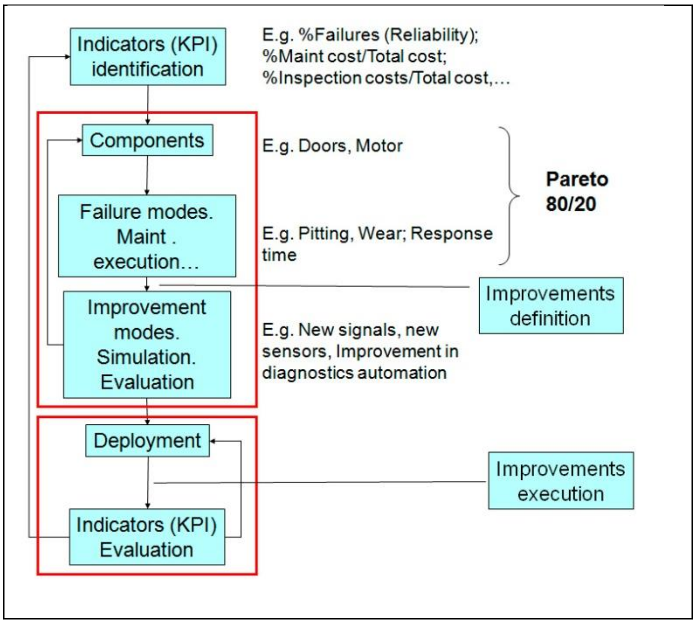

Figure 2. Deming cycle adapted for PdM strategies improvement

The selected strategy is implemented at least in one control group in order to evaluate the results. New procedures, hardware and software technologies will be deployed and tested. Using the initially defined KPIs, the assessment will evaluate whether the initial objectives have been fulfilled or not.

If the objectives are not fulfilled, i.e. there are large deviations from the simulated cost assessment, it is necessary to return back to the previous step and identify the deviations sources. If the objectives are being fulfilled, new objectives can be defined to follow with the continuous improvement programme, starting in this case a new cycle. The frequency of cycles is not predefined and it depends of the information collected about objective fulfilment.

3. Asset management simulation

The reliability information on which the maintenance strategies simulator relies on is the probability density distribution of failure for the system or component. Such a function determines the possibility of a failure occurring at a given time. It is typically established from test or run-time data noticing the time at which failure occurs, also from calculated and/or existing reliability data.

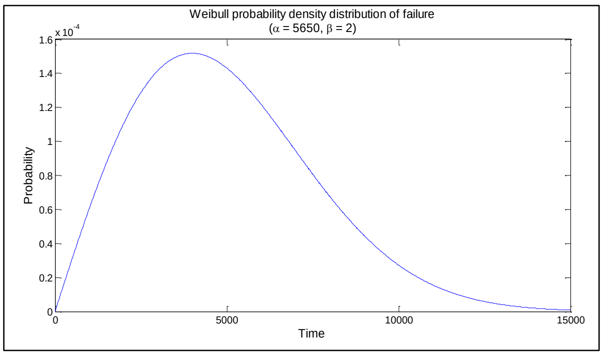

Figure 3. Example of Weibull probability density function

The Weibull distribution is frequently employed because it is applicable to different phases in the life of a component or system. Weibull distribution is described by three parameters: scale (α), shape (β) and location (γ). The higher the scale value the longer the life expectancy of a component. The shape factor distinguishes among early-type failures ($\beta < 1$), random-type failures as during useful life ($\beta = 1$), and wear-type failures ($\beta > 1$). In the first case ($\beta < 1$) failure rate decreases with time. It is constant for $\beta = 1$, and for $\beta > 1$ it increases with time. Finally, the location parameter affects the origin of the time axis and it usually is set to zero. Weibull distribution is flexible enough to model a variety of failure occurrence that are decreasing, increasing or constant, allowing it to describe any phase of a component's lifetime.

Given this function it is possible to apply Monte Carlo method for performing a random sampling and as a consequence for obtaining possible times at which failure occurs. A known way to do so is with the inverse of the cumulative Weibull distribution function, by means of performing a random sampling for it in order to obtain times of failure. As the process is repeated the series of values obtained produce a more faithful description of the Weibull distribution.

With this methodology it is possible to obtain a time of occurrence of a failure and, therefore to anticipate the type and number of maintenance actions performed following a particular maintenance strategy and their result in terms of cost. This process is repeated for the Monte Carlo analysis to offer a faithful description, and time and costs accumulated. The cost per unit time is used in order to compare the results obtained with different maintenance strategies. In our approach we have only considered Weibull distribution due to its flexibility, but any other failure distribution could be used in the simulation process if the degradation component model is known.

The following maintenance strategies have been considered for simulation:

- **Corrective:** maintenance actions are performed only when a failure occurs.
- **Preventive:** besides corrective maintenance actions, additional systematic maintenance actions are performed every pre-defined time interval.
  It is assumed that after corrective actions are performed the time interval should be reset (as good as new), as it is often the case with, for example, oil replacement.
- **Inspection:** additional maintenance actions are performed based on the results of a failure detection analysis every pre-defined time interval done by maintenance personnel.
- **Predictive:** maintenance actions performed based on the results of a failure detection analysis every pre-defined time interval. In this case the action is done by a laboratory (off-line), or technology integrated in the system/component (on-line).

Moreover in a combined strategy, maintenance actions are performed according to the four aforementioned strategies. This is to say, besides corrective maintenance actions, systematic preventive maintenance is performed along with inspections, and more frequent, failure detection analyses.

3.1. Simulating a predictive maintenance strategy

The approach for simulating the application of a predictive strategy in maintenance involves establishing beforehand the error rate for the failure detection analysis. Typically this error rate consists of a probability of false positives and a probability of false negatives. The former corresponds to the situation in which the analysis generates a false alarm, this is to say, the analysis detects a failure when it is actually not the case. The later corresponds to the opposite situation, in which the analysis does not detect a failure when it actually exists. The occurrence of false positives/negatives is simulated with a Monte Carlo analysis by means of a random sampling from a uniform distribution. If the value resulting from this random sampling is lower than the probability of false positives/negatives, the occurrence of a false positive/negative is indicated.

The approach for the predictive maintenance strategy simulation is a loop devised as follows. First, Monte Carlo analysis on Weibull function provides the time at which the next failure is assumed to occur.

Next, the detection analyses until the last before failure or the end of useful life are checked. It any produces a false alarm then the process is stopped, the time of occurrence registered and the cost of the analyses performed is allocated to maintenance costs. Note that the last detection analysis before failure is not considered in this process because it is not affected by false alarms.

The time registered (failure, false alarm, or end of useful life) is accumulated as usage time of the system.

If the accumulated time is equal to the end of useful life of the system, a replacement/refurbishment maintenance action is performed, with assumption that the system will be as good as new afterwards. The cost of the action is allocated to maintenance costs.

If a false alarm has occurred, a repair maintenance action is performed and the cost allocated to maintenance costs. Note that maintenance costs will include the cost of the detection analyses as well, as explained above.

If, otherwise, the last detection analysis before has been reached:

It is checked whether it is a false negative and, if it is, a corrective maintenance action is performed, assuming the system will be as good as new afterwards. The cost of the action is allocated to maintenance costs, which include as well the cost of the detection analyses as explained above.

Otherwise, this is to say it is not a false negative, the detection analysis has succeed in detecting a failure. A repair maintenance action is performed (assuming just before the instant of failure, thus making the most of the productive time, although in a real case the prediction horizon may not be as exact or ample). The cost of the action is allocated to maintenance costs which include, as explained before, the cost of the detection analyses performed.

This procedure is repeated from the beginning until a production time and number of repetitions stipulated have been reached.

Finally, as a result, the cost per time unit for the simulated maintenance strategy is calculated.

To sum up, Table 1 shows the data necessary for simulating the process.

Table 1. Data for the simulation of the predictive strategy

Type	Data	Description
General	Production hours	Total simulated time (e.g. a number of times the useful life of the system/component)
	Useful life	Useful life of the system/component
	Replacement cost	Cost of replacement/refurbishment of the system/component at the end of useful life
Reliability	Scale, shape, location	Parameters describing the Weibull function
Corrective	Failure cost	Cost of unexpected failures requiring unscheduled maintenance
Predictive	Action cost	Cost of performing a failure detection analysis
	Action interval	Predefined time interval for performing failure detection analysis
	Repair cost	Cost of dealing with a failure detected by the failure detection analysis
	False positive probability	Probability of the failure detection analysis generating a false alarm
	False negative probability	Probability of the failure detection analysis missing an actual failure

Given this process simulation for predictive strategy, the next step is to provide a decision support system to establish the optimal maintenance policy to be performed on the asset. This optimal policy is determined through the calculation of the following strategies, selecting the one which provides a minimum cost:

a. Corrective strategy
b. Preventive strategy with optimal frequency of replacement task
c. Predictive strategy with optimal frequency of inspections, sampling or measurement. In this case different approaches could be considered.

As a result, the optimal strategy for selected asset is provided according to cost and reliability information provided.

4. Results and Impact

4.1. Results with respect to existing models

The developed simulator has been compared with an existing previous model [9]. This model is devised as a set of equations for calculating maintenance costs using similar data and reliability function with Monte Carlo analysis. However, the model works on the aggregated number of failures per period (e.g. preventive maintenance interval), whereas the simulator develops the appearance of failures in the maintenance process as time unfolds. With this simulation mechanism we can introduce conditions, events, decisions or actions associated with a failure or between failures. For example, in the case of preventive maintenance strategy, it is assumed by the simulator that after corrective actions are performed the systematic preventive time interval should be reset, as it is often the case with, for example, oil replacement.

As shown in Table 2, this situation can be included in the simulator and it results in economic savings in our case. In addition to this, table 2 shows very similar results between the simulator en the model in corrective, inspection and predictive strategies, when using the same data. Notice that [9] does not consider the possibility of having different probability for false positives and negatives as it works with accuracy. We have also generalized the concept of predictive maintenance to include, besides on-line sensors, inspections and off-line laboratory analysis. Besides this, we have additionally developed the combined strategy for the simulator.

Furthermore, Exakt tools make focus on calculating the optimal frequency for preventive maintenance task through an accurate failure prediction as well as to support decision on perform maintenance replacement or not, always taking into account operating and condition variables. In this sense, the proposed simulation is complementary and proposes the optimal strategy to perform on the asset.

The improvement is being used to monitor several improvement cycles at this moment in many different systems, such as machine-tools, wind-mill gearboxes or elevators. Having in mind the initial reliability KPIs and once identified the main contributors to this KPI inefficiencies at step 1 (Identification of objectives). The step 2 (Identification of the most important product/processes) focuses on different aspects of these systems, such as spindle, gear-box and door-mechanism among others, as main contributors to such inefficiencies (In this case, there is a directly link to unreliability or failures no.).

Table 2. Results for the simulator compared with Berdinyazov [9]. Weibull $\alpha = 52048$ and $\beta=1$.

Berdinyazov [9]	Cost per unit time	Cost per unit time	Simulator
Corrective	1.5	1.5	Corrective
Preventive	4.7	4.4	Preventive
Inspection	15.2	15.1	Inspection
Predictive	1.5	1.5	Predictive

4.2. Impact on improved OEM quality of services

Selecting these critical elements allows a detailed study of the principal failures and causes at step 3 (Analysis of selected product/processes), using information of FMEA combined with information analysis of the machinery population.

The analysis at these products has been focused on technologies and processes with potential to identify the failure before it happened and with the help of the work team knowledge different systems were found to solve failures with different degrees of confidence and coverage of the different failure modes (e.g. a costly particle sensor can be much more accurate than a periodic inspection of the lubricant, but the degree of cost-effectiveness varies depending the Mean Time Between failures - MTBF, the cost of the inspection and of the sensor, etc.).

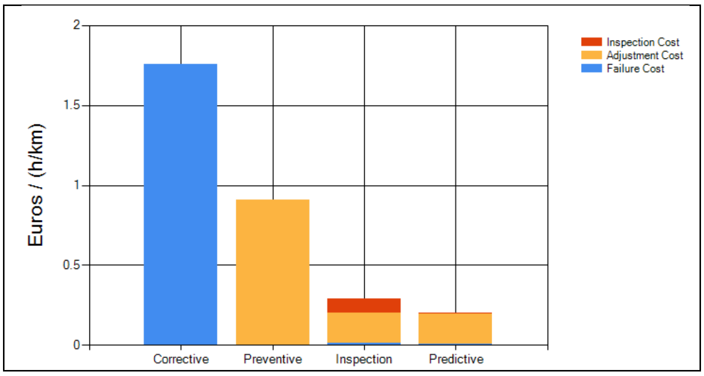

Figure 4. Impact of different strategies of maintenance of a mechatronic component within a system, taking into account a global KPI (cost) segmented at three different cost categories (Cost of repair and loss of revenues when the component fail; cost of the preventive activities; and cost of the monitoring activities -whether remote or on-site)

The improvement analysis finishes with the estimation of the potential impact of the different strategies (corrective, time based, inspections) measured in Euro's, comparing the maximum cost of the selected technologies and alternative strategies, considering several known or estimated variables such as frequency of the inspections, reliability, cost of failures, inspections and preventive actions. A typical representation can be in figure Figure **4**.

These estimations allow different questions to be asked, such as,

- What is the cost target for a sensor if we want to implement a remote monitoring system?
- Which accuracy should have the sensor?
- Which is the best inspection frequency if we prefer this option?
- What is more cost effective – corrective or preventive strategies?

In summary, this approach provides a framework to compare different strategies in a structured methodology and simulation will be realistic depending on the supported reliability and cost information. For instance, reliability data could take into account potential hazards in the operational environment such as the use of equipment.

4.3. Impact on improved quality of information

Improvement cycle is not only focused on optimizing the maintenance processes, it is also related to the process of information acquisition and storage as well as in the identification of best indicators for finding deficiencies, which in other ways could be difficult to analyse.

Firstly, the improvement of the information is very much related to the analysis of the first steps in the cycle. For instance, it is normal to notice a single indicator (usually related somehow to machinery reliability or availability) as initial KPI. During the project development of new indicators are discovered and these always carry specific actions to access to new sources of information necessary to evaluate the indicators. This targeted search of specific information within the company, while running the improvement cycle, is much more rewarding than an initial global search of all the available information.

A typical increase in the number of indicators and associated KPIs is as follow

Table 3. KPI evolution

KPI	Description	Source of information
Reliability	Number of failures –	This is typically available from the first moment in maintenance as well as in OEM, but in many cases is incomplete (only part of the failures is known)
Availability	Time machine is up and running in perfect conditions	Normally requires productivity information not easily reachable by maintenance personnel, nor OEM
Maintenance cost		Costs (materials, personnel, …)
Wrench time	Time needed to perform one action (corrective, preventive) excluding non-productive activities	Detailed maintenance information, need of portable tools to collect appropriate data
Quality of Service	Delays, customer opinion	Different sources – somehow linked to 'perceptions' rather than real facts.

On the other hand, the initial assessment with a reduced feedback express clearly the information lacks that the organization may have. For instance, an example may be to improve the way the failures are managed (e.g. to reduce the amount of incidences not yet linked with a clear type of failure). Vaguely defined fields of the work order may be erased ("Other" type of failures) when a clear and consolidated FMECA analysis is shared between engineering and maintenance areas. Clearer codes concerning failure-cause-action can be addressed through the initial improvement cycles.

5. Conclusions and further work

This paper has presented how simulation tools can help identifying a new PdM approach in the cost-benefit of the product life cycle or plant productivity. This approach depends on several types of data probably not available at the beginning, and it has to be supported by a continuous improvement model also described in this paper. The process of information acquisition and storage as well as in the identification of best indicators are key for finding deficiencies, which in other ways could be difficult to analyse.

Furthermore, in the process of automation the continuous improvement cycle, a previous step can be added where the simulation is performed from different ontologies containing information of the selected asset:

- Structural information
- Failure Modes and effects
- Costs during life cycle
- Detectability by sensing or inspections

In this work the Weibull distribution is calculated from a database that contains information on faults, at the component level, and the target would be to go achieve the optimal strategy at failure model level, since adding sensors in predictive strategies would avoid some specific failure modes. Also providing asset tree structure enables the simulation at different levels, having a new set combination to perform the selection of the most cost-effective maintenance strategy.

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8.2 A multi-objective hybrid EDA-based algorithm for optimizing preventive maintenance plans

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Resumen

Este artículo presenta un algoritmo multiobjetivo híbrido basado en EDA (MOHEDA) para resolver el problema de optimización combinatoria en la definición de los planes de mantenimiento preventivo en términos de costes de inspección y duración equilibrada de los planes, que además cumple con las diferentes restricciones legales impuestas por los estándares internacionales y regulaciones en seguridad. El objetivo es una definición más precisa de los planes para reducir los costes de mantenimiento, utilizando un enfoque híbrido de métodos de optimización que alimenten un algoritmo evolutivo como EDA. Los resultados obtenidos indican que el enfoque MOHEDA reduce significativamente el tiempo de búsqueda en el espacio y proporciona un método valioso para definir los planes de mantenimiento para una flota de activos.

A multi-objective hybrid EDA-based algorithm for optimizing preventive maintenance plans

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Abstract. This paper presents a multi-objective hybrid EDA-based algorithm (MOHEDA) to solve the combinatorial optimization problem in the optimization of preventive maintenance plans in terms of inspections costs, which also complies with different legal restrictions imposed by international standards and local government regulations, such as safety requirements. The objective is a more accurate definition of plans to reduce maintenance costs, using a hybrid approach of optimization methods feeding an evolutionary algorithm like EDA. This algorithm solves this problem given the huge search space. The ability of the proposed algorithm in providing an efficient solution is evaluated by means of a set of use cases related to the optimization of maintenance complex fleets. The obtained results indicate that MOHEDA approach significantly reduces the search time in space and provides a valuable method to define the maintenance plans for a fleet of assets.

Keywords: Preventive maintenance, multi-objective optimization, estimation of distribution algorithm, prescriptive analytics

1 Introduction

Advances being experienced in last decades in different industrial and service fields are based in part on the correct performance of the associated assets, without unscheduled interruptions or unexpected failures. In this context, the growing interest in safety, higher quality, better sustainability and preservation of goods, together with pressure to increase efficiency, make an effect on the importance of maintaining systems to guarantee optimal performance during its operational lifetime. This situation pushes maintenance managers towards preventive maintenance strategies (such as replacement, periodic readjustment, etc.) where automatic assessment of the condition of assets stands out thanks to the technological support.

As the pressure for more efficient asset management increases, also is increasing the search for reliable and cost-effective ways to monitor condition. In this pursuit, digitalization is key, to limit as much as possible the manual inspection, replacement or repair processes of assets that are in good condition, to minimize costs and ensure the maintenance and efficient operation of assets. However, there are still many aspects that must be worked on to achieve automated systems. For example, the need to provide robust and reliable support system over time to the asset maintainer for their decision-making.

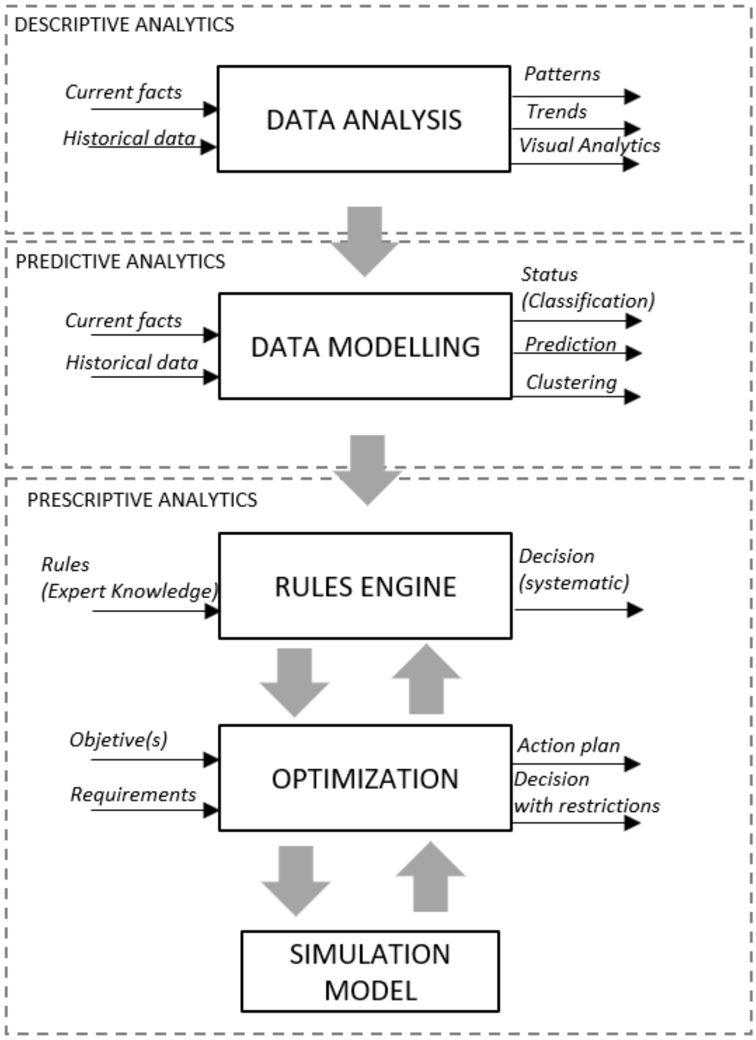

Fig. 1. Prescriptive analytics techniques and their support on Descriptive and Predictive analytics.

This digitalization opens the door to different levels of data analysis in support of business improvement: Whereas the application of descriptive analytics allows a first understanding of the current state of an asset, and with predictive analytics we can make estimations of its potential degradation, there is a third level of analytics -prescriptive- as a natural extension to these processes, which leads to complete integration of the predictive information with the business aspects of the maintenance processes [1]. The emerging technology of prescriptive analytics goes beyond descriptive and predictive models by recommending one or more courses of action –and showing the likely outcome of each decision [2]. Through prescriptions, recommendations are made about actions to be taken to reduce costs or improve benefits. For example, in case of predictive maintenance of a fleet of vehicles or wind turbines, replacing periodic reviews or repairs on failure events with a system that recommends the best time to perform the review of each component, thus reducing costs for breakdowns and repairs. The Prescriptive analytics considers how decisions affect costs and benefits accounts, and what restrictions and considerations should be considered in the actions that are going to be carried out. This automatically generates realistic action policies that have a direct impact on benefits.

The discipline of prescriptive analytics is based on all the knowledge and techniques of descriptive and predictive analytics (classification, prediction and clustering), also drawing from fields such as operational research and numerical optimization (see **Fig. 1**).

1) Descriptive Analytics: Use the data to explain the past. It involves preparing and analyzing historical data to identify patterns and trends. Techniques such as regression models, data modeling, and visualization are often used in Descriptive Analytics.
2) Predictive Analytics: Use the data to determine what may happen in the future. Predictive Analytics allows the probability associated with future events to be determined from the analysis of the available information (present and past), in addition to discovering relationships between the data that is not normally detected with a less sophisticated analysis. Techniques such as data mining and predictive models are used.
3) Prescriptive Analytics: Use the data to prescribe those actions that increase our chances of obtaining the best results. Prescriptive Analytics determines new ways of operating that allow us to achieve our business objectives. Techniques such as optimization or simulation are used, although the creation of a prior predictive model is normally required.

On the other hand, maintenance research and development are gaining importance worldwide because of the irruption of technologies that enable advanced maintenance solutions, including prescriptive analytics techniques. Maintenance management involves different concepts and activities [3]: Part of the literature deals with (a) development and selection of optimum maintenance strategies [3][4][6]; other major areas of research describe (b) the modelling and programming of the machine maintenance [6] and (c) the theory of reliability, replacement and the determination of frequency of inspection [7]; finally, other researchers concentrate on (d) simulations to measure a maintenance system [8].

In this paper our objective is to focus on a problem related to maintenance strategies that is scarcely tackled so far in literature: It is related to the development of standardized maintenance plans related to Preventive Maintenance (PM) tasks, in complex maintenance scenarios with different fleet characteristics as well as maintenance resources. These scenarios appear in areas such as fleet transport systems (buses, trains), infrastructures, or lifts. Here, PM tasks should be identified and developed to manage the failure. PM tasks are value-added tasks conducted using the least labor, downtime, and materials to complete the tasks. Therefore, fleet maintenance requires standardized job plans. And the definition of plans concerning the PM tasks to be done by maintenance personnel is a crucial problem prior to resource planning.

The development of these plans is not trivial. Product maintenance specifications can include up to hundreds of different actions, to be executed with different frequencies, and with some differences depending on product versions. On the other hand, not all maintenance personnel is able to execute all actions (e.g. some specific repair and inspection tasks can only be performed by senior specialists) and there may be even different contracts regarding the frequency of inspections depending on the SLA (service level of agreement contracted) or the country legislation, to name only some examples.

There are several prescriptive analytic approaches that deal with this problem For instance, Bevilacqua & Braglia [9] describe an application of the Analytic Hierarchy Process (AHP) for selecting the best maintenance strategy for an important Italian oil refinery. Gilabert et al [10] present a methodology based on Monte Carlo simulation for selecting the most cost-effective maintenance strategy. Das Chagas et al propose a multi-objective genetic algorithm for determining Risk-based inspection programs [11]. Then, in this work, a novel method to address the optimization challenge by means of a new algorithm (MOHEDA) which define standardized maintenance plans adjusting maintenance inspection time and balancing the different visits. This work improves/overcomes some of the previous work [13].

The rest of this paper is organized as follows. Section 2 introduces multi-criteria optimization methods. Section 3 details the problem statement and formulation of a multi-objective optimization of maintenance plans. Section 4 shows the proposed hybrid EDA-based architecture and the specific algorithms inside. Then, in Section 5 MOHEDA is applied to optimize lift fleet maintenance plans. Finally, Section 6 provides some concluding remarks.

2 Multi-criteria optimization

In many cases, the decision process is not systematic, but framed in a context defined by a series of restrictions. These restrictions set the conditions for a decision to be valid, but there are many valid decisions in the same context. Usually when making these decisions, there is implicit a way of assessing the quality of one decision over another, using an objective function that allows to distinguish the best solution from a set of other valid solutions.

These characteristics fits as a challenge for automated decision-making trough expert optimization models. Decision making tools help users to improve the ability of solving problems and the capabilities of production systems [13][14]. Optimization is also linked to decision-making, minimizing the maintenance costs or the ecological impact [16]. Usually, the optimization of maintenance plans cannot be solved by accurate optimization algorithms, which are those that guarantee finding an optimal solution as computational time can disable this option.

This fact has a consequence in the scientific community: it is the born of meta-heuristics techniques, which are approximate algorithms of optimization and general-purpose searches. Despite not finding the optimal solution, meta-heuristic techniques ensure that there is a good solution identified within a reasonable execution time. Therefore, there can be multiple optimization criteria simultaneously depending on the needs. It is possible to have different optimization systems or include commitments for calculations with partially connected criteria.

Focus so far on maintenance optimization has been mainly based on single criterion techniques (SCO), however authors have remarked the need to consider two or more criteria at same time, creating a need for multi-criteria optimization (MCO) techniques. Initial investigations have shown that there are many explorations into MCO algorithms for maintenance. Almeida et al [16] performed a review on multi-criteria and multi-objective models for maintenance and reliability applications, presenting a classification of models, tools and techniques. Syan & Ramsoobag [18] also presented an outlook of MCO techniques used for solving maintenance problems, indicating limitations and strengths of a particular MCO technique in relation to its application for solving maintenance issues.

In recent years, metaheuristics techniques like Evolutionary Algorithms (EAs) are common applied as solvers of MCO problems, including genetic algorithms (GAs), simulated annealing, and taboo search which have been widely used in conjunction with simulation to improve the effectiveness of the search procedure. Among these guided search methods, simulation optimization through GA is an active area of research. There are successful applications of this type in processes such as facility layouts; planning an assembly line; managing a supply chain; Kanban systems; the selection of maintenance policies; and spare parts inventory management [19].

Estimation of Distribution Algorithms (EDAs)[20] refer to a kind of novel EAs mainly based on probabilistic modeling instead of genetic operators such as crossover or mutation. The main mechanism is to conduct searching by sampling new generations from a probability distribution, which is estimated based on some selected promising individuals in the current population. The major advantage of EDAs is that they can explicitly learn the dependences among variables of the problem to be solved and use this structural information to efficiently generate new individuals. Moreover, it is not necessary to adjust a high number of parameters like in GAs. It has been shown in previous work that EDAs can outperform traditional EAs on a number of difficult benchmark problems [21].

The optimization methods addressed to tackle maintenance planning that appears in literature are varied: Some of the optimization criteria are related to smoothing the preventive maintenance work load of the maintenance personnel [21], other related to short-term and long term [3] scheduling of planned maintenance work. Hybrid optimization has been also used in maintenance for determining periodic inspections [22]. Instead, this paper is centered in optimizing the group of tasks to be done by the maintenance personnel in a fleet, considering that having too much different task plans could be difficult to be managed by the staff.

3 Problem statement and formulation

A maintenance plan is defined as a set of multiple tasks performed on an asset. For instance, in case of a car could be (a) check tire pressure, (b) change oil and filters, and many other tasks with a defined duration and frequency. The definition and realization of these tasks (i.e. frequency) depend on the configuration of the assets, complying also with the corresponding legislations. Theoretically the optimal solution would consist of defining a specific maintenance plan for each different asset type. In any case, that solution is not feasible, since the technician in charge of performing maintenance tasks cannot have a specific plan for each asset, which can complicate the understanding and execution of each plan, leading to inefficiencies (e.g. wrench time) and could even provoke errors related to the maintenance process execution. Moreover, the assignment of technicians to maintenance plans is not evident, as there is a minimum profile requested to be able to carry out a plan. Finally, the frequency requested in the performance on some tasks (e.g. monthly, quarterly, yearly based) implies that the grouping of activities (e.g. into what it is called 'Visits' or 'Inspections') is an important factor to take into account when dealing with efficient planning.

In the end, a better solution is to define a single plan (or a reduced set of plans) because the maintenance personnel can perform the tasks efficiently. For this reason, maintenance plans must be standardized for all assets with similar configuration, location or owner, even if this implies the execution of tasks that are not strictly necessary on certain assets [10]. Likewise, the equalization of the maintenance plans over a certain asset group is important as this enables efficient plan scheduling, and in particular the assignment of resources –i.e. human labor- at system level (e.g. a fleet, park, neighborhood, city, etc. serviced by a maintenance center). In conclusion, several maintenance factors or policies have an influence and must be considered when making the definition of the plans. These considerations suppose a problem of combinatorial optimization. The optimization problem must take into account the following factors, considering that it applies to a set of assets of a similar configuration:

1) Maintenance tasks (T^m): Each asset has a set of tasks to execute depending on its configuration.

$$T^{m} = (t_1, \dots, t_n) \quad (1)$$

where n is the total number of tasks and t_n the duration of the task.

2) Client contract (T^c): The asset belongs to a client, that depending on the contract can have certain additional tasks.

$$T^{c} = (t_1, \dots, t_l) \quad (2)$$

3) The final set of preventive maintenance tasks (T) is the union of T^m and T^c.

$$T = T^{m} \cup T^{c} \quad (3)$$

4) Preventive maintenance frequency (F): Each task has a minimum required frequency which depends on different legislations (F^l), safety criteria (F^s) or customer requests (F^c).

$$F = (min\{F_1^l, F_1^s, F_1^c\}, \dots, min\{F_n^l, F_n^s, F_n^c\}) \quad (4)$$

5) Maintenance personnel profiles (W): maintenance personnel performs some tasks depending on their skills.

$$W = \left(w_{1,1}, \dots, w_{1,k};\ w_{j,1}, \dots, w_{j,k}\right) \quad (5)$$

where j is the number of maintenance personnel profiles and k the total number of preventive maintenance tasks. Each element $w_{j,k}$ of W is either 0 or 1. If $w_{j,k} = 1$ then the maintenance personnel can perform the tasks.

6) Plans (P): The tasks to be executed on an asset in a visit, are grouped in different plans, due to their different frequency requirements.

$$P = (p_1 t_1, \dots, p_1 t_1;\ p_n t_n, \dots, p_n t_n) \quad (6)$$

where n is the total number of maintenance tasks. Each element p_n of P is either 0 or 1. If $p_n = 1$ then the tasks are included in the plan.

7) Schedule (S): The plans to be performed annually are grouped in a maintenance schedule.

$$S = (P_1, \dots, P_m) \quad (7)$$

8) Visits (V^p): The maintenance of an asset requires *m* plans carried out in *V* visits and by a certain maintenance personnel skill (w_j). Obtaining the number of visits associated with each plan is another optimization problem.

$$V^p = (v_1, \dots, v_m) \quad (8)$$

$$V = \sum_{i=1}^{m} v_i \quad (9)$$

9) Maximum plan duration (*MP*): MP is a restriction indicated by maintenance manager.
10) Unbalance parameter (*U*): the maximum difference of minutes between plans, also defined by the maintenance manager.

The main reason of using a multi-objective is due to 2 different objectives are managed at the same time:

1. The minimization of the total time required to perform one plan on the asset, that is, the sum of all tasks in visits. This optimization affects to every plan.

$$f_1 = min \left\{ \sum_{i=1}^{m} \left(\sum_{j=1}^{n} p_j t_j \right) v_i \right\} \quad (10)$$

where *m* is the number of plans, *n* the number of tasks related to plan *i*, t_j the duration of task j, p_j indicates if t_j is included in the maintenance plan, and v_i the number of visits of plan *i*.

2. The minimization of differences in duration among the different plans (maximum balance)

$$f_2 = \min \left\{ \max_i \left\{ \sum_{j=1}^{n} p_j t_j \right\} - \min_i \left\{ \sum_{j=1}^{n} p_j t_j \right\} \right\} \quad (11)$$

4 Proposed multi-objective hybrid EDA-based algorithm

In a multi-objective optimization, it is not easy to find a solution which optimizes all function objectives at same time, or that solution does not exists. Therefore, a set of possible solution must be obtained instead of having a unique solution covering single objectives. Once the set is obtained, the maintenance manager can choose any of the solution based on their preferences or company policies.

In this work, MOHEDA is developed to minimize the total time of performing maintenance tasks (which implies minimizing total cost) and minimize the differences among plant durations (or maximizing balance). MOHEDA also tries to solve two different optimization problems. On the one hand, searching the best combination between number of plans and number of visits for each plan (V^p). The restrictions defined by the maintenance manager only provides the total number of plans (*m*) and visits related to the asset (V). For instance, the requirements could be 2 plans in 6 visits, and the algorithm must give as a result that Plan 1 (P_1) should be done in 2 visits (v_1=2) and Plan 2 (P_2) in 4 visits (v_2=4), or maybe other combination as 1-5(v_1=1;v_2=5) or (v_1=3;v_2=3). On the other hand, MOHEDA searches the best standardization of tasks in the plans/visits to perform (S), according to the input requirements (T, F, W, m) and restrictions (MP, B), guided by the objective functions f_1 and f_2.

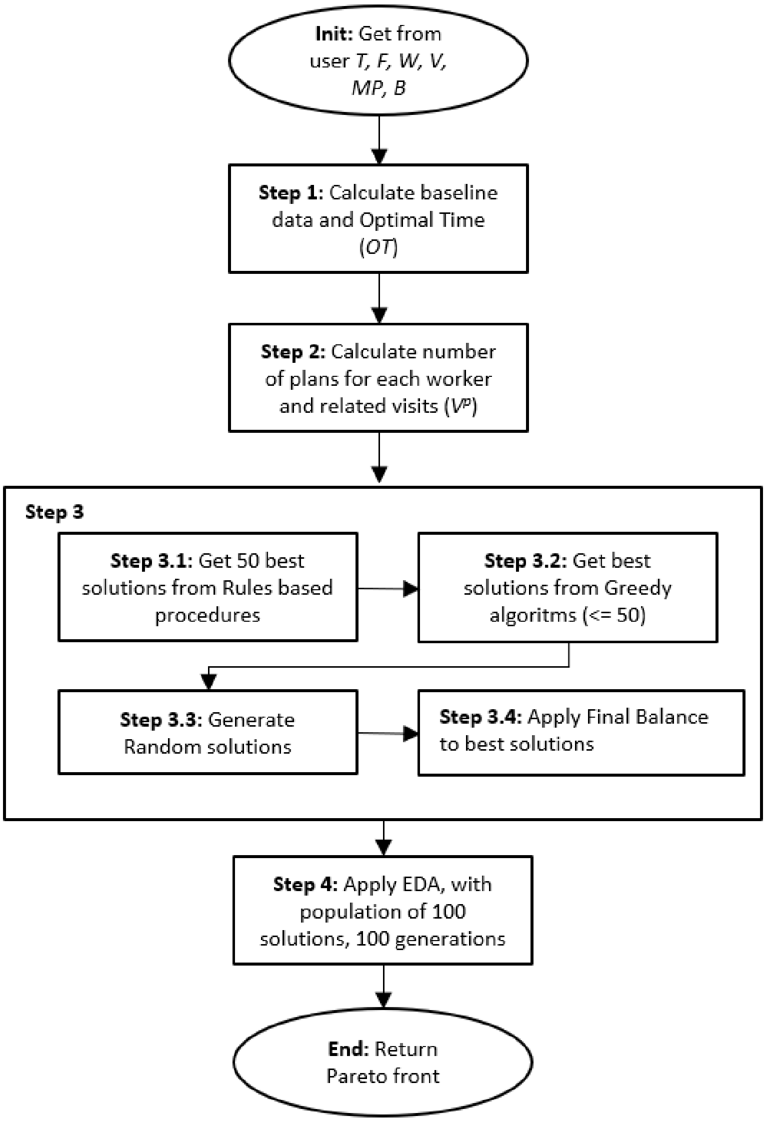

Fig. 2. Multi-objective Hybrid EDA-based optimization algorithm architecture.

Fig. 2 depicts the algorithm architecture used in the EDA optimization. During the optimization, the tasks are assigned to the maintenance plans, which have previously been defined with certain number of visits. This process is done in 4 different algorithms, obtaining as a result the best plan provided after the execution of:

1) Rules procedure minimizing time.
2) Rules procedure balancing plans.
3) Greedy algorithm minimizing time.
4) Greedy algorithm balancing plans.

After that, EDA is applied during 100 generations using as initial population the set of 50 solutions obtained in the previous step. Finally, MOHEDA returns the Pareto front of optimal solutions found. In this way, the search space to be explored by MOHEDA is reduced, finding a good enough optimal solutions in a reasonable computation time (< 5 minutes). Next points describe in detail the different steps of the algorithm.

4.1 Baseline data (Step 1)

During the first step the input information must be provided by the maintenance manager to perform the maintenance plan optimization. In detail:

1) Main asset configuration. The concept of a plan standardization is not to provide the specific configuration, but it should be defined in an upper level (e.g. in case of cars, they could be gas or diesel, involving different maintenance tasks). This returns a specific T^m .
2) Country legislation. Usually countries specify different frequency inspections related to maintenance tasks (F^l).
3) Client contract type, the levels of SLA. For instance: Low cost, Standard and Premium. This contract type defines T^c and F^c.
4) Maintenance personnel profiles, in relation with their skills. For instance, Technician and Specialist (*W*).
5) For each maintenance personnel profile, number of maintenance plans that can execute, and total visits by year (*V*).
6) Maximum duration of a maintenance plan, in minutes (*MP*).
7) Maximum difference among plan durations in minutes (*U*), in order to provide balanced plans.

According to the previous inputs, the baseline data is obtained. This data consists of a set of tasks and their compulsory visits for each task. The Optimal Time is defined as the sum of these task durations multiplied by their visits.

$$OT = \sum_{i=1}^{i=n} t_i \, v_i \qquad (12)$$

where m is the total number of tasks, t_i is the duration of the task and v_i the minimum number of visits of t_i. This Optimal Time will be used for validation purposes. The evaluation criterion is defined as the difference between the Total Time of an annual maintenance plan and their Optimal Time.

$$TT = \sum_{i=1}^{i=m} \sum_{j=1}^{j=n} p_j t_j v_i \tag{13}$$

$$D = TT - OT \tag{14}$$

4.2 Plans Vs Visits (Step 2)

As introduced before, obtaining the number of visits associated with each plan is another optimization problem. The maintenance of an asset requires *m* plans carried out by a skill-enabled maintenance personnel in V visits. This is calculated in Step 4 by other execution of the set of Rules & Greedy algorithms used to generate the initial population. However, this execution is performed in a small number of iterations in case of the Greedy algorithm (< 10).

The target of Plans & Visits process consists in selecting the most appropriate plans vs. visits relation so that the search is more limited, and the search algorithm starts from a pre-selected configuration. This step starts with the calculation of all possible combinations of visits and plans by maintenance personnel profiles. For example, for a Specialist profile, 3 plans and 6 visits (Specialist-3-6), the number of visits of each plan could be: 1-1-4; 1-2-3; 2-2-2. For each possible combination, the Step 4 is executed with 10 iterations. The best result obtained (E.g. 1-2-3), is the configuration used in the next step.

4.3 Rules Procedures (Step 3.1)

The rules procedures are 2 simple heuristic algorithms used to search intuitively a good set of solutions. These algorithms can also find the optimal solution for simple use cases. This first procedure follows the sequence of **Fig. 3**. The Rule procedure is executed 25 times win different Unbalance criterion (*U* = 0, 2, 4, ...,50)

1) Tasks are ordered from largest to smallest duration.
2) Sequentially, each task is assigned to a plan, using this algorithm:
   a) Selection of possible candidate plans: do not include the task previously and meet the maintenance personnel profile requirement.
   b) Select the plan where the number of times matches the number of visits of the task, or in its absence the smallest absolute difference.
   c) In case of a tie, the plan with the minor number of visits is selected.

RuleProcedure (T, F, W, V^p, P, U)

$T^s(x)$ = Sort(T)

For $x = 0, 1, \ldots x \leq n$

$P'(y)$ = Candidates (P, W, V^p, U)

For y = 0, 1, …y ≤ max(y)

If ($V^p(y) = F(x)$)

$P(x, P'(y)) = 1$

Exit for

If not any $P(x) = 1$

y = SortByVisitsDifferenceFirst ($V^p, T^s(x)$)

$P(x,y) = 1$

Return P

Fig. 3. Pseudocode of Rules Procedures

The second procedure follows a similar sequence, except in case of tie in last step: the plan with the minor duration is selected in this case. This change produces a more balanced result.

4.4 Greedy algorithms (Step 3.2)

The greedy algorithm is an intuitive algorithm used in optimization problems. The algorithm makes the optimal choice at each step as it attempts to find the overall optimal way to solve the entire problem. For its implementation, we have selected a backtracking algorithm as the search mechanism. This technique is the direct application of the search method known as ***first in depth***, although using a heuristic criterion in every step. The algorithm consists of:

1) Select an option among the possible ones.
2) For each selection, order them using a heuristic criterion and consider the possible options recursively, in a loop (search ***first in depth***).
3) When the stop condition is reached, return the best solution found of all evaluated solutions.

In our case, the first greedy algorithm performs this sequence (see **Fig. 4)**:

1) If a task can be carried out by several profiles, all the possibilities are considered.
2) Combinatorial search of assignment of all possible tasks to each visit is done. That is, a visit could be considered as an empty box where the different combination of tasks is inserted.

The second greedy algorithm is similar except it works with sorted visits: in each search iteration, the visits are sorted by their absolute difference between the number of visits of the task and the number of visits of plan, prioritizing a maximum balance among the plans.

```
GreedyAlgorithm (T, F, W, V^p, P, cont)
  If (cont > max_cont or isOptimum(P))
        AddBestSolution (P) ← Keep maximum 25 best solutions in global variable
  else if isEmpty(T)
        AddBestSolution (P)
  else
     T^s(x) = Sort(T)
     For x = 0, 1, …x ≤ n
        P'(y) = Candidates (P, W, V^p )
        For y = 0, 1, …y ≤ max(y)
              P (x, P'(y)) = 1
              T' = Remove T from T^s
              GreedyAlgorithm (T', F, W, V^p, P, cont+1)
Return P
```

Fig. 4. Pseudocode of Greedy Algorithm

4.5 Generate random individuals (Step 3.3)

The Rules procedures returns 50 solutions, but the Greedy algorithms could provide less than 50 individuals. The initial population is defined as 100 individuals, therefore in some cases is necessary to generate new individuals. The procedure to generate new solutions selects randomly an individual, make a copy, and perform *r* mutations on it. The used number of mutations (*r*) is 5. After that, the news solutions generated are modified to keep the feasibility and consistency with frequency tasks required (*F*) and maintenance personnel profiles (*W*).

4.6 Final Balance (Step 3.4)

The Final Balance consists of 2 procedures which works with the found solution, trying to improve it. The final balance follows this sequence:

1) A greedy algorithm that tries to remove the tasks of the plans that exceed the maximum allowed according flattening criterion (*U*) or the longest in case of not having it. It moves them to the plans of shorter duration.
2) If the flattening criterion (*U*) is not yet met, another greedy algorithm adds unrealized tasks to the plans of shorted duration. This Final Balance is applied in the execution of the 4 algorithms implemented in Step 4.1 and 4.2.

4.7 EDA procedure (Step 4)

The probabilistic model used for EDA is the algorithm UMDA (Univariate Marginal Distribution Algorithm), specifically, in each generation the joint probability distribution that serves to estimate the behavior of the selected individuals, is factorized as a product of univariate and independent distributions (see **Fig. 5**).

$$p_l(x) = p(x \mid D_{l-1}^{Se}) = \prod_{i=1}^{n} p_l(x_i) = \prod_{i=1}^{n} \frac{\sum_{j=1}^{N} \delta_j(X_i = x_i | D_{l-1}^{Se})}{N} \quad (15)$$

EDA (UMDA)

D_0 ← 100 solutions from Rules & Greedy algorithms

Repeat for l=1, 2, … until 1000th generation

D_{l-1}^{Se} ← Select best 50 solutions from D_{l-1}

$p_l(x) = p(x|D_{l-1}^{Se})$ ← To estimate the distribution probability of selected solutions

D_l ← To sample 50 solutions (new generation) from p(x)

End repeat

Fig. 5. Pseudocode of UMDA

The selection of best 50 solutions are based con Pareto property. First, for each solution is calculated the number of individuals which dominate the solution. Next, the set of 100 solutions is sorted by this dominance parameter, removing the 50 last solutions. A solution is an array of 2 values, TT and U (16). A solution s_1 dominates another solution s_2 if $TT_1 < TT_1$ and $U_1 < U_2$.

$$s_i = \{TT_i, U_i\} \quad (16)$$

5 Application example: lift fleet maintenance optimization

Lifts systems are extensively used in a variety of buildings and other infrastructures. They are regularly serviced by the maintenance personnel to guarantee a smooth, safe, and uninterrupted operation. To maintain the quality of service as well as the maintenance efficiency optimization tools are very important. The main objective is always to maximize service level reducing the maintenance cost. Optimizing the number of lifts that each technician can maintain involves prior steps related to variability of lifts models, standardization of tasks and maintenance personnel skills.

To standardize jobs of the maintenance personnel is key, since having too personalized maintenance for each lift model could be counterproductive. Even tough personal digital assistants can ease task scheduling, the optimization of task execution – the maintenance plan involving e.g. a predefined sequence of operation – is critical to reach efficient maintenance rates as well as minimizing risks. There are however some distinctions that are needed to take into account. For instance, lift models are grouped into electrical and hydraulic lifts to simplify tasks. However, standardization of maintenance visits is one of the objectives of the optimization. Other factors that have been considered are categorization of maintenance personnel and the balancing of different visits duration. This issue can be very important to facilitate the tasks of other optimization tools related to maintenance routes and global strategies.

MOHEDA has been validated using lift fleet job standardization. In this use case, two types of lifts are considered: electrical and hydraulic. Moreover, the maintenance personnel are categorized into Specialists and Technicians. Due to a user requirement, a short execution time is needed, and the execution of greedy instances has been limited to 1000 iterations, enabling an execution time minor than 5 minutes. **Table 1** details the set of 10 different use cases executed to test MOHEDA. The different columns specify the identification number, the lift type, the country or region, the skills involved to optimize, the number of desired plans and the number of compulsory visits due to legal or contractual considerations.

Table 1. Set of use cases that compose the lift fleet job standardization

Nº	Type	Country/ Region	Skills	Plans	Visits
#1	Electric	1	Sp	3	6
#2	Electric	1	Sp	2	6
#3	Electric	1	Sp	4	12
#4	Electric	2	Sp	3	9
#5	Hydraulic	2	Sp	3	12
#6	Electric	2	Sp/Tc	2/1	9
#7	Electric	3	Sp	2	6
#8	Electric	3	Sp	3	6
#9	Electric	4	Sp	4	12
#10	Hydraulic	5	Sp	3	9
#11	Electric	6	Sp	2	12
#12	Electric	6	Sp/Tc	2/1	2/10

Table 2. MOHEDA parameters

Parameter	Value
Number of generations	1000
Population Size	100
Number of mutations	5
Greedy iterations	10000

Table 2 presents the parameters used for MOHEDA executions. In order to evaluate the stochastic behavior of MOHEDA, 50 executions have been performed using use case #1. The descriptive statistics results of numbers of solutions in Pareto front are shown in **Table 3**, with a mean of 28,72 and standard deviation of 1,0698.

Table 3. Results of stocastic behavior

Statistics	**#Solutions**
Minimum	27
Maximum	31
Mean	28.72
Median	29
Std. dev.	1.0698

Use case #1 corresponds to a country that presents a lot of diversity in their maintenance plans, and the maintenance company needs to standardize the plans to solve the problem of diversity. The maintenance inspection are made 6 times, by one specialist ($V = 6$). The Optimal Time (OT) is 148.95 minutes (minimum yearly maintenance 'process' time to be spent per asset – excluding other potential time expenditures, such as transport between assets). The execution of MOHEDA require 4 minutes to return the Pareto front using a Windows 10 PC, Intel Core^{TM} i5 7500 3.4 GHz and 16 Gb of RAM. **Fig. 6** presents the Pareto front of MOHEDA with the sets of optimal solutions found.

Table 4 provides the 2 optimal solutions found according to the objective functions F_1 (minimizing Total Time) and F_2 (minimizing Unbalance). These 2 optimal solutions present significative differences. F_1 provides 3 different plans which Total Time matching the Optimal Time. This implies an Unbalance of 21.12 minutes among the different plans P_i. Which is due to P_1 being significantly shorter in duration than P_2 and P_3. On the other hand, F_2 provides a perfect balanced solution but 62.51 of extra time by asset per year in relation with the F_1 solution. Actually, using F_2 solution implies an increase of 41% in maintenance time comparing with F_1 solution, and therefore a similar increment in maintenance cost. For this reason, the lift maintenance company should consider an intermediate solution from the Pareto front which provides MOHEDA, being possible to translate these results to an estimation of maintenance cost. The increased cost of any other F_x solution over F_1 solution is evaluated by maintenance center specialists as it allows to save money in learning, to reduce human mistakes caused by having too much different plans, and to simplify maintenance planning and personnel load balancing.

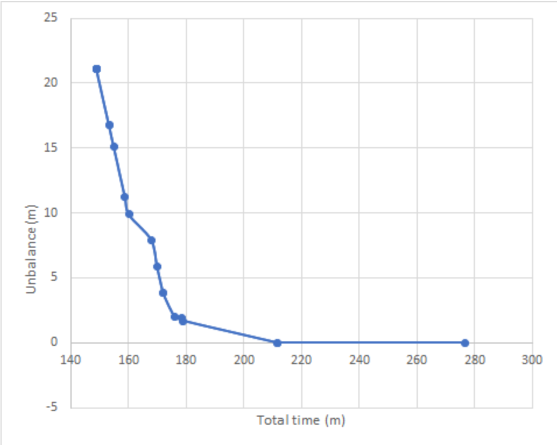

Fig. 6. Pareto front of use case #1.

Table 4. Pareto front ends in #1 use case with MOHEDA, where Plans (P_1, P_2, P_3) are all assigned to Sp(ecialist) with a specific frequency of visits (V_1, V_2, V_3)

Objective (F_x)	**P_1 Sp V_1=4**	**P_2 Sp V_2=1**	**P_3 Sp V_3=1**	**Total Time (TT)**	**Difference (D)**	**Unbalance (U)**
F_1	17.49	38.91	38.90	148.95	0	21.12
F_2	35.25	35.24	35.24	211.46	+62.51	0.01

Those solutions have been compared with the solutions found by the 4 algorithms used to generate the first generation in the EDA step. **Table 5** shows how MOHEDA can find more balanced solutions than those 4 algorithms when optimizing Total Time (F_1) and **Table 6** present the results optimizing F_2, which in this case are quite similar. Even MOHEDA has been compared with other implementation of EDA using individuals randomly generated in first generation, which are remarkable improved in both objective functions. In sum, combined MOHEDA approach clearly provides improved results over the different algorithms working in isolated mode.

Table 5. Comparison of MOHEDA results in use case #1 minimizing Total Time (F_1)

Objective F_1	**P_1 Sp V_1=4**	**P_2 Sp V_2=1**	**P_3 Sp V_3=1**	**Total Time (TT)**	**Difference (D)**	**Unbalance (U)**
MOHEDA	17.49	38.91	38.90	148.95	0	21.12
Rules Op.	17.79	49.96	27.84	148.95	0	32.17
Greedy Op.	49.96	27.84	17.79	148.95	0	30.17
EDA random.	28.20	38.31	43.43	194.55	+45.60	15.23

Table 6. Comparison of MOHEDA results in use case #1 minimizing Unbalance (F_2)

Objective F_2	P_1 **Sp** V_1**=3**	P_2 **Sp** V_2**=2**	P_3 **Sp** V_3**=1**	**Total Time (*TT*)**	**Difference (*D*)**	**Unbalance (*U*)**
MOHEDA	29.13	29.13	29.14	174.81	+25.86	0.01
Rules B.	29.13	29.13	29.14	174.81	+25.86	0.01
Greedy B.	29.14	29.14	29.13	174.81	+25.86	0.01
EDA random	36.81	36.56	36.81	220.60	+71.65	0.25

Table 7 shows the results obtained by F_1 and F_2 functions with MOHEDA in 10 different use cases, compared with the best results provided by the set of 4 Rules & Greedy procedures used to generate the initial population for EDA. MOHEDA gets a mean improvement in balance of 40.12% in F_1 function. Considering F_2, MOHEDA has also provided a mean improvement in Total Time of 5.31%.

Table 7. Comparison of results between MOHEDA and the Rules & Greedy procedures

	MOHEDA		**Rules & Greedy**	
Experiment	F_1 ***TT/U***	F_2 ***TT/U***	F_1 ***TT/U***	F_2 ***TT/U***
#1	148.95/**21.12**	211.46/0.01	148.95/32.17	211.46/0.01
#2	171.07/32.17	203.25/0.01	171.07/32,17	203.25/0.01
#3	255.68/**14.08**	371.13/0	255.68/32.17	371.13/0
#4	231.68/**23.24**	**358.70**/0.02	231.68/35.29	502.83/0
#5	367.80/**24.39**	**490.26**/0.01	367.80/41.31	490.29/0.01
#6	171.98/0.01	171.98/0.01	171.98/43.82	171.98/0.01
#7	182.89/38.08	220.97/0	182.89/38.08	220.97/0
#8	157.31/**25.29**	**190.63**/1.84	157.31/38.08	232.89/0.01
#9	279.03/**17.03**	**428.21**/0.07	279.03/37.05	432.48/0.01
#10	217.53/29.04	310.04/0.02	217.53/50.19	310.04/0.02

MOHEDA also shows how using different maintenance personnel profiles allows a significantly improvement in maintenance times and costs. This improvement is more evident as the complexity increases, for instance when dealing with a higher number of visits (e.g. in use cases #3, #5, #9 & #11) and when dealing with multiple worker profiles (as in use cases #6 & #12). In particular, we may focus on the use case #11 where the Specialist executes the maintenance every month during a year, setting only 2 different plans. In an annual maintenance, the first plan is executed every 6 months and the second one the rest of months. OT is 380.40 minutes. The initial results are shown in **Table 8**. Considering the main objective of minimizing time, results indicates an overrun of 13.33 minutes at least.

The use case #11 considers the situation where the Specialist executes the maintenance every month during a year, setting only 2 different plans. In an annual maintenance, the first plan is executed every 6 months and the second one the rest of months. OT is 380.40 minutes. The initial results are shown in **Table 8**. Considering the main objective of minimizing time, results indicates an overrun of 13.33 minutes at least.

Table 8. Pareto front ends in use case #11 with MOHEDA

Objective (F_x)	***P₁*** **Sp V_1=10**	***P₂*** **Sp V_2=2**	**Total Time (TT)**	**Difference (D)**	**Unbalance (U)**
F_1	28.20	55.87	**393.73**	**+13.33**	27.67
F_2	41.79	42.58	530.03	+149.63	0.79

In the use case #12 the main objective is to save money using two different maintenance personnel profiles (Specialist and Technician). The Specialist executes 2 plans every 6 months, and the technician executes 1 plan in 10 visits. Table 4 shows how the Specialist skill improves the time while keeping the basic tasks duration, related to previous situation in **Table 9**.

Table 9. Pareto front ends in use case #12 with MOHEDA

Objective (F_x)	***P_1*** **Sp V_1=1**	***P_2*** **Sp V_2=1**	***P_3*** **Tc V_3=10**	**Total Time (TT)**	**Difference (D)**	**Unbalance (U)**
F_1	49.21	49.20	28.20	**380.40**	**0**	0.01
F_2	45.25	45.25	36.15	451.97	+71.57	0

This result means a significantly improvement of 13 minutes by lift. Assuming a lift fleet of 100 units and considering that technician cost/hour is 40% less than using the specialist maintainer, the savings are close to 32% in this use case.

6 Conclusions

In this paper, an original MOHEDA algorithm is presented which can provide a decision-making tool to optimize the maintenance inspections costs in terms of time and balance (minimizing unbalance) which also complies with different legal restrictions imposed by international standards and local government regulations, such as safety requirements. This algorithm is completely scalable in number of tasks, plans, visits and maintenance personnel profiles. Using a multi-objective algorithm allows to support a maintenance company in the identification of optimum preventive maintenance plans, reducing costs or enabling an easier later scheduling. The Hybrid approach of MOHEDA improves the results obtained in comparison with the execution of EDA, Rules and Greedy procedures isolated. This algorithm has been applied to a set of 10 different use cases to demonstrate this significantly improvement. In this way, MOHEDA explores the search space in a more efficient way. The experimentation also presents how the use of MOHEDA helps maintenance engineer assess different balanced maintenance plans and providing a reduction of maintenance costs using different maintenance personnel profiles. MOHEDA can also be used in other planning problems within the industry, such as optimization of production (resources, energy demand, minimization of waste, etc.) whenever there are business rules that can be instantiated in the combinatorial model. As future work, the algorithm will be improved with more base optimizers, and will be applied in other maintenance applications.

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8.3 Semantic web services for distributed intelligence

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Resumen

Este capítulo presenta una plataforma de servicios web semánticos lista para integrar capacidades de procesamiento inteligente conforme a la arquitectura de sistemas abiertos para mantenimiento basado en condición (OSA-CBM). Esta plataforma forma parte de una infraestructura de comunicación flexible, llamada DYNAWeb, donde también se integran sensores inteligentes inalámbricos, dispositivos móviles inteligentes y los sistemas de mantenimiento preexistentes de las compañías.

CHAPTER 11

Semantic Web services for distributed intelligence

Eduardo Gilabert, Alexandre Voisin

This chapter presents a Semantic Web services platform ready to integrate intelligent processing capabilities according to Open Systems Architecture for Condition Based Maintenance (OSA-CBM) architecture. This platform is part of a flexible communication infrastructure, nicknamed DynaWeb, where a generic wireless device is being also developed between novel sensors, smart PDAs and existing maintenance systems of the companies.

11.1 Introduction

The Semantic Web is a project that intends to create a universal medium for information exchange by giving meaning (semantics), in a manner understandable by machines, to the content of documents on the web. Under the direction of the Web's creator, Tim Berners-Lee of the World Wide Web Consortium, the Semantic Web extends the World Wide Web through the use of standards, markup languages and related processing tools (Berners-Lee 2001).

Currently web pages are designed to be read by humans, not machines. The Semantic Web aims to make web pages understandable by computers, so that they can search websites and perform actions in a standardized way. The potential benefits are that computers can harness the enormous network of information and services on the web.

11.2 State-of-art in semantic web application to industrial automation

A review of current knowledge automation status is indicated with respect to semantic web, including current efforts in providing common reasoning mechanism and current models on web semantics applied to industrial world.

11.2.1 What is an Ontology?

In the context of knowledge sharing (Gruber 1992), the term ontology is used to mean a *specification of a conceptualisation*. That is, ontology is a description, like a formal specification of a program, of the concepts and relationships that can exist for an agent or a community of agents. This definition is consistent with the usage of ontology as set-of-concept-definitions, but more general. And it is certainly a different sense of the word than its use in philosophy.

What is important is what ontology is *for*. Ontologies have been designed for the purpose of enabling knowledge sharing and reuse. In that context, ontology is a specification used for making ontological commitments.

For pragmatic reasons, people choose to write ontology as a set of definitions of formal vocabulary. Although this isn't the only way to specify a conceptualisation, it has some nice properties for knowledge sharing among Artificial Intelligence (AI) software (e.g., semantics independent of reader and context). Practically, an ontological commitment is an agreement to use a vocabulary (i.e., ask queries and make assertions) in a way that is consistent (but not complete) with respect to the theory specified by an ontology. We build agents that commit to ontologies. We design ontologies so we can share knowledge with and among these agents.

11.2.2 Advantages of Semantic Web techniques

The Semantic Web (SW) offers many advantages over previous web technologies that make web applications more useful and human independent, but also, its use could increase companies' profits since SW techniques improve the efficiency of these applications. The main advantages are described below (Carro 2005).

11.2.2.1 Improved web search

The first clear advantage of Semantic Web techniques is the potential of improving web search since SW mechanisms allow for a better analysis of the items to be found. Nowadays, the keyword or word spotting searching is based on true-false results. Ontology-based searching uses the relationships and axioms of concepts, thus it can filter some seemingly appropriate but not desired results and add some seemingly different but actually same results. For instance, if you look for unleaded petrol, your search engine can expand the search to 95 or 98 octane unleaded petrol if both of them are derived from the concept 'unleaded petrol' in the associated ontology. Moreover, this SW-enabled search engines would not only be able to search the object in the language of the query, but also in other languages because the system understands what the user wants.

In this way, Semantic Web technologies enable a search engine to better understand what you are looking for and increase the precision of the returned results. This is especially important in companies who have to deal with a large amount of data. SW-enabled search engines are also especially advantageous in intranets of large companies, because the business of the companies is focused on certain domains where it can be possible to define suitable ontologies.

11.2.2.2 Better integration

The second main advantage of SW techniques is a higher potential to integrate different components. Business partners are enabled to better understand the syntax and semantics of their documents, to exchange them, and to transfer them into the appropriate application for further automatic processing without human intervention. This also includes appropriate mapping or translation mechanisms. However, even humans can take advantage of a better integration, since ontologies can model relationships between the participants of such a process so they can uncover the hidden structure. Also on the software developer side, a higher degree of integration could also promote software component reusing in addition to a higher degree of automation.

11.2.2.3 Lexicon flexibility and standardisation

Theoretically, ontology mappings and translation allows users to flexibly choose the words they like. A generic ontology would facilitate the mapping and translations of ontologies. All ontologies would be mapped to this generic one and this generic one would be mapped to all of them. There will be a leak of precision but less ontologies translators would be necessary. It could be also used for standardizing the concepts, and improving the communications between different partners.

11.2.2.4 Composition of complex systems

In Semantic-Web enabled systems, it is possible to compose numerous Web services and Web contents to produce one more complex system. Several SW technologies could be combined to develop a complex system with further functionalities.

11.2.3 Semantic web languages

The Semantic Web is comprised of the standards and tools of XML, XML Schema, RDF, RDF Schema and OWL. The OWL Web Ontology Language Overview describes the function and relationship of each of these components of the Semantic Web:

- XML provides a surface syntax for structured documents, but imposes no semantic constraints on the meaning of these documents.
- XML Schema is a language for restricting the structure of XML documents.
- RDF is a simple data model for referring to objects ("resources") and how they are related. An RDF-based model can be represented in XML syntax.

- RDF Schema is a vocabulary for describing properties and classes of RDF resources, with a semantics for generalization-hierarchies of such properties and classes.
- DAML is a language created by DARPA (Hendler 2000) as an ontology and inference language based upon RDF. DAML takes RDF Schema a step further, by giving us more in depth properties and classes. DAML allows one to be even more expressive than with RDF Schema, and brings us back on track with our Semantic Web discussion by providing some simple terms for creating inferences.
- DAML+OIL: A successor language to DAML and OIL that combines features of both.
- OWL adds more vocabulary for describing properties and classes: among others, relations between classes (e.g. disjointness), cardinality (e.g. "exactly one"), equality, richer typing of properties, characteristics of properties (e.g. symmetry), and enumerated classes.

11.2.4 Semantic web platforms

The most popular semantic web platform are described in the following paragraphs.

11.2.4.1 Protégé 2000

Protégé 2000 (Noy 2000) is probably the best-known ontology development and knowledge acquisition environment. It was developed by Stanford Medical Informatics group of Stanford University. Protege has mainly three functions:

- construction of domain ontologies,
- customization of knowledge acquisition forms, together with extensions for graphical widgets for tables, diagrams and other components and
- a library which other applications can use to access and display knowledge bases.

The main idea behind the functions is to make the knowledge representation format adaptable for various ontology languages, whereas other ontology modelling tools tend to choose some specific languages to concentrate on.

The Protégé-OWL editor is an extension of Protégé that supports OWL. The Protégé-OWL editor enables users to:

- load and save OWL and RDF ontologies,
- edit and visualize classes, properties and SWRL rules,
- define logical class characteristics as OWL expressions,
- execute reasoners such as description logic classifiers and
- edit OWL individuals for Semantic Web markup.

Protégé-OWL has an open-source Java API for the development of custom-tailored user interface components or arbitrary Semantic Web services.

11.2.4.2 Altova Semantic Works 2008

Altova Semantic Works 2008 is the visual RDF/OWL editor from the creators of XMLSpy. Visually design Semantic Web instance documents, vocabularies, and ontologies then output them in either RDF/XML or N-triples formats. This software works with tabs for instances, properties, classes, etc., context-sensitive entry helpers, and automatic format checking.

Semantic Works 2008 allows the user to graphically create and edit RDF instance documents, RDFS vocabularies, and OWL ontologies with full syntax checking. Context-sensitive entry helpers are presented with a list of permitted choices based on the RDF or OWL dialect (figure 11.1).

Semantic Works 2008 provides functionality for:

- visual creation and editing of RDF, RDF Schema (RDFS), OWL Lite, OWL DL, and OWL Full documents using an intuitive, visual interface and drag-and-drop functionality,
- syntax checking to ensure conformance with the RDF/XML specifications,
- auto-generation and editing of RDF/XML or N-triples formats based on visual RDF/OWL design and
- printing the graphical RDF and OWL representations to create documentation for Semantic Web implementations.

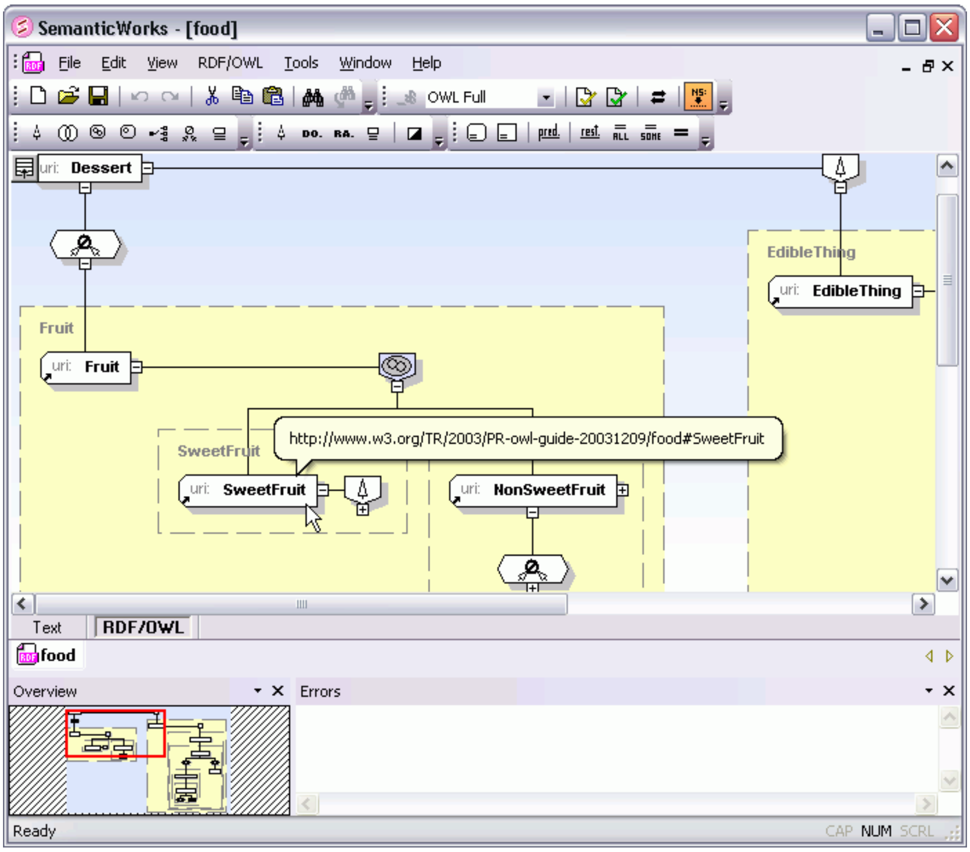

Fig. 11.1 Defining an ontology with Altova Semantic works

11.2.4.3 SMORE

SMORE is designed to enable users to markup HTML documents in OWL using Web Ontologies (figure 11.2). Primary goals include:

- to allow the user to markup web documents with limited knowledge of OWL terms and syntax,
- to provide a way to use Classes, Properties, and Individuals from existing ontologies, do limited ontology editing, or even create a new ontology from scratch using terms from web documents and
- to provide a flexible environment to create simple web page simultaneously with markup.

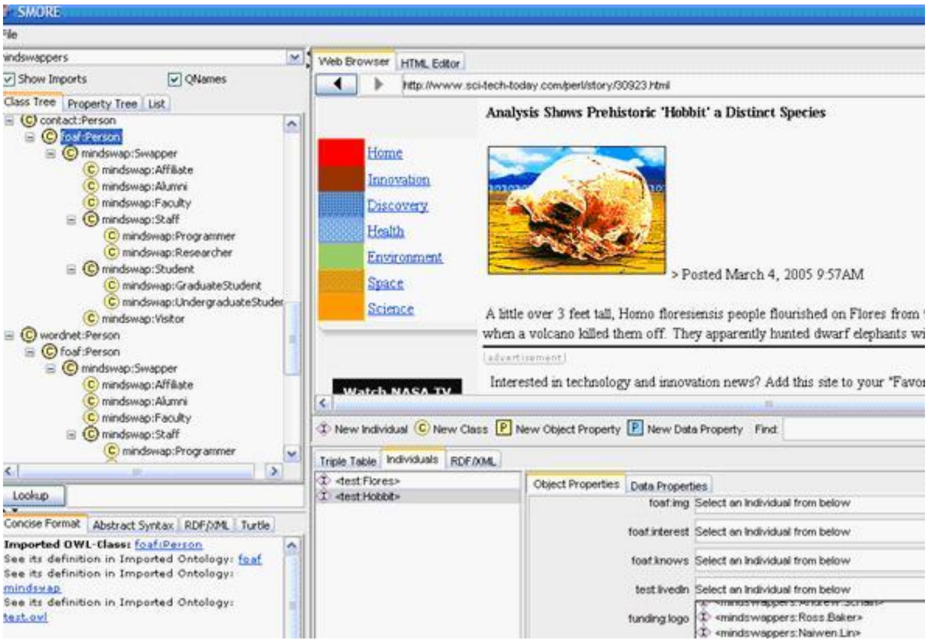

Fig. 11.2 SMORE user interface

11.2.5 Semantic web development in industrial automation

In industrial environments semantic web developments have been performed, as explained in next paragraphs.

11.2.5.1 OntoServ.NET

OntoServ. NET (Terziyan 2003) is a framework for industrial semantics-enabled maintenance services organized in peer-to-peer network of services platform. It is based on web services and semantic web technologies and meant to provide solution for building large-scale industrial maintenance networks. It is automated maintenance system, which can integrate maintenance-related information from many sources, highly desired in order to give appropriate maintenance support. The goal is to improve the performance of the filed device management process by launching a network of distributed intelligent maintenance services (figure 11.3).

OntoServ.NET implements the benefits of:

- Semantic Web (interoperability based on ontological support and semantic annotations),

- Intelligent Web Services (modelling, automated discovery and integration) and
- (Multi)Agents technologies (agents communication, coordination and mobility).

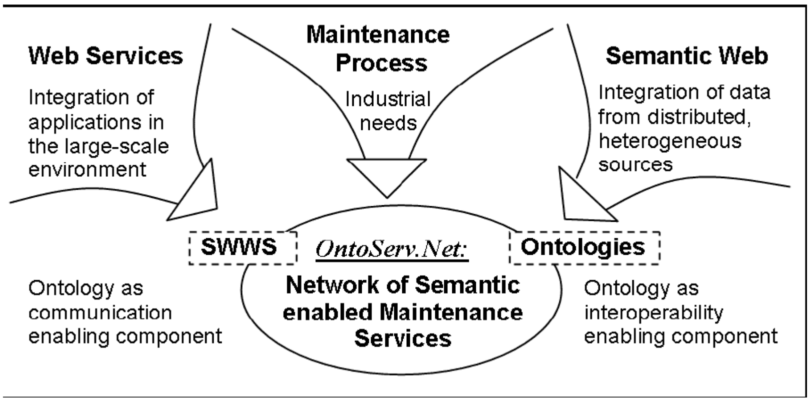

Fig.11.3 Ontoserv.Net structure

11.2.5.2 Obelix

OBELIX (Ontology-Based ELectronic Integration of CompleX Products and Value Chains) has developed an e-business ontology tool suite and library to support smart collaborative e-business and the realization of innovative applications (Akkermans 2004). The Obelix tool suite consists of an ontology server providing facilities for editing, component brokering, ontology management, and web language import and export, plus a number of ontology-based tools including an e-business scenario analysis and simulation tool for DVC models and strategies, an automatic product classifier to speed up application of content management standards, and a multi-product configuration tool for online collaborative design scenarios. In addition, Obelix has delivered a modular e-business ontology library. The tools has been validated through three e-business applications: e-markets for energy trading and servicing, new digital music value chains, and online design of events.

11.2.5.3 Rewerse

Rewerse is a research Network of Excellence on "Reasoning on the Web" (Bry 2004) that is funded by the European Commission and Switzerland within the 6th Framework Programme. The main objective of Rewerse is to provide tangible technological bases for an industrial software development of advanced web systems and applications.

Rewerse involved during 4 years (2004-2008) 27 European research and industry organisations from 14 European countries and about 100 computer science researchers and professionals playing key roles in applied reasoning. One goal of Rewerse was to spread and support the use of reasoning techniques in advanced web applications and systems. It focused on creating a competitive advantage for the European industry.

11.2.5.4 Knowledge web

Knowledge Web (Eisenstadt 2000) is a 4 year Network of Excellence project (2004-2008) funded by the European Commission 6th Framework Programme. Supporting the transition process of ontology technology from academia to industry is the main and major goal of knowledge web.

The mission of Knowledge Web was to strengthen the European industry and service providers in one of the most important areas of current computer technology: semantic web enabled e-work and e-commerce. The project concentrates its efforts around the outreach of this technology to industry. Naturally, this includes education and research efforts to ensure the durability of impact and support of industry.

Fig. 11.4 Knowledge web main areas

In comparison with Rewerse, both networks have decided to focus on different application scenarios:

- Knowledge Web: Semantic web services

• Rewerse: Reasoning on geographical / time-related data, Bioinformatics, personalized information systems

However, more use cases have been collected in Knowledge Web.

11.2.5.5 Other related works

In (Posada 2005) an ontology was used as an improvement for building an industrial plant through a graphic design software. It associates the semantics to the geometric parts from CAD (Computer-Aided Design) reconstruction. It uses semantic compression added to simplification techniques of the geometrical data to increase the efficiency. The ontology has been developed using Protégé 2000.

In airspace systems, (Valente 2005) presents an architecture for operating unnamed aerial vehicles that leverages a group of military information ontologies to semantically specify and compose information services. The ontologies were developed with Ontolgy Web Language (OWL) and cover a wide range of content including definitions of military information, organizations and communications

11.3 Web services for dynamic condition based maintenance

Web services are a well known technology which is taken into use in industrial environments. They offer interoperability between independent software applications over Internet by means of Simple Object Access Protocol (SOAP) which enables the communication.

The advantages of web services are the central issue in DynaWeb. Different software modules are able to communicate among them in order to perform a specific task. In this context, to provide the most convenient analysis flow, information processing is understood as a distributed and collaborative system, where there are different levels of entities that can undertake intelligence tasks. Given this, a system architecture has been defined to identify the interactions between actors and the required functions, including 4 layers that correspond to the central information processing layers of OSA-CBM standard (Arnaiz 2009,Bengtsson 2003,Lebold 2002):

1. **Condition monitoring:** It is related to state detection. This layer receives measurements from sensors and their signal processing software. These measurements have to be compared to expected values, and alert should be generated in case of anomaly detection, due to values outside from preset limits or changes in the usual trend.
2. **Health assessment:** The main function of this layer is to set the current health of the asset, in case of an anomaly detected by condition monitor-

ing modules. It generates health records proposing possible faults, based on health history, operational status and maintenance tasks history. One of the existing diagnosis processes is based on previously developed systems (Gilabert 2006) using Bayesian networks to facilitate a model that can work with uncertainty and can also be adapted with feedback information.

3. **Prognostics:** This module takes into account data from all the prior layers. The primary focus of the prognostic module is to calculate the future health of an asset, with account taken to the future usage profiles. The module reports the failure health status of a specified time or the remaining useful life.
4. **Decision support:** Is in this context related to scheduling. A computerised maintenance management system schedules work orders based on component predictions. After that it distributes work orders to different operators (PDAs). The PDAs need to read the smart tags in order to learn about the components (Adgar 2007).

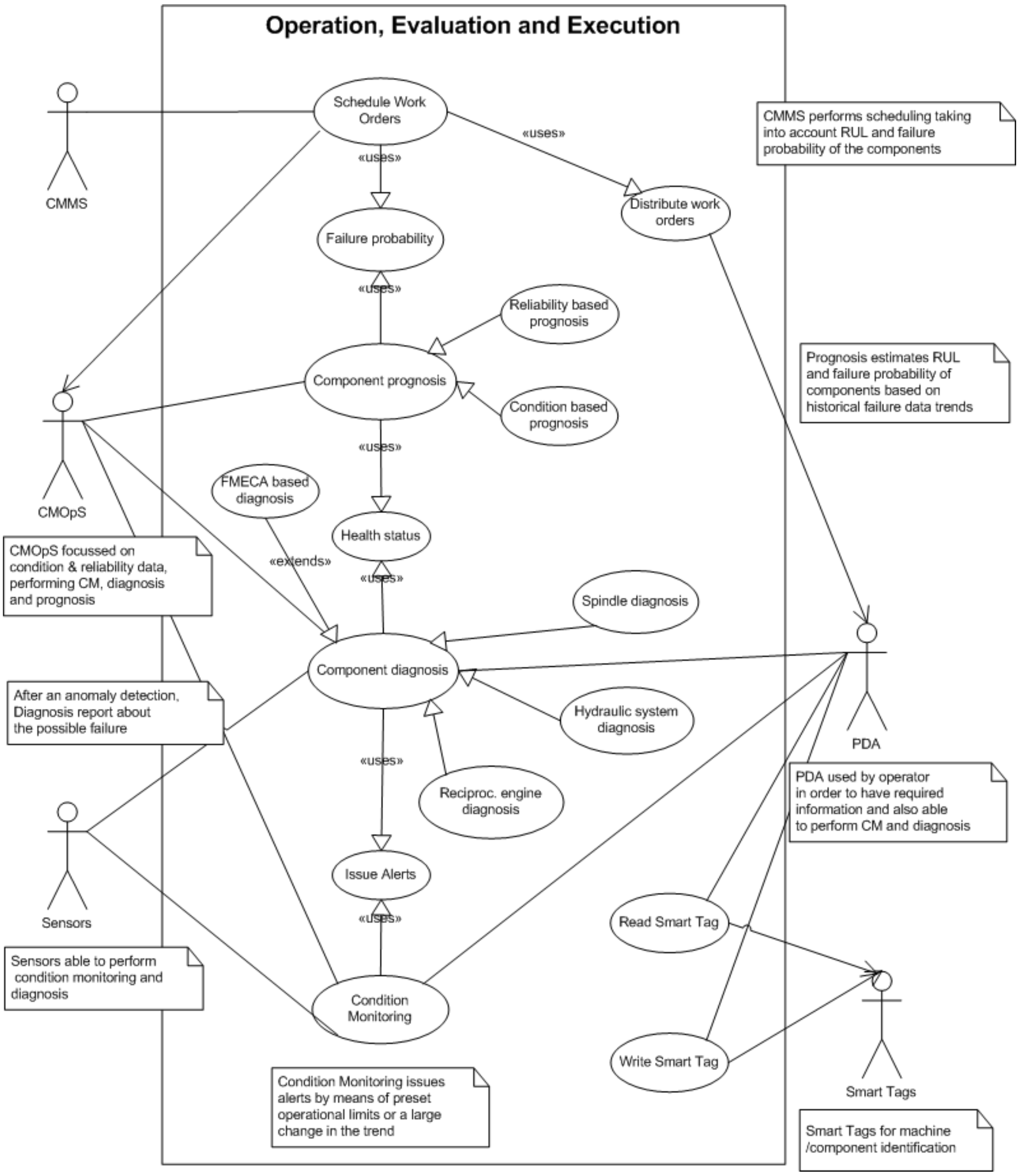

Fig. 11.5 Use case diagram for operation, evaluation and execution

One of the challenges is to match the semantic web concept to the maintenance function. In this way, information used over Internet must be specified in ontologies. The ontology represents the knowledge in Internet (Fensel 2001), defining in a formal way the concepts of the different domains and relationships, with ability to perform reasoning over this knowledge. In this case the definition of ontologies has been performed starting from the standard CRIS defined by MIMOSA. CRIS represents a static view of the data produced by a CBM system, where every OSA-CBM layer has been associated to ontology (Lebold 2002).

OSA-CBM was developed around MIMOSA CRIS that provides coverage of the information (data) that will be managed within a condition based maintenance system. It defines a relational database schema with about 400 tables for machinery maintenance information. In short, CRIS is the core of MIMOSA which aims to the development and publication of open conventions for information exchange between plant and machinery maintenance information systems, and Dynamite web services are built using CRIS standard for interoperability and internal information processing.

Another great challenge is to approach this concept for everyday computing resources (e.g. SMEs), as well as for the forthcoming mobile services. In this sense, with regard to the usage of these web services, there are three main elements defined which take part in the communication:

- Human Machine Interfaces (HMI) actor, that is, a software interface for the operator sitting at the desk or walking with the PDA and interacting with local or central database systems asking web services to process specific information.
- Agent for communicating with DynaWeb web services. The agent is able to get the needed data from other sources, translating it into the ontology language. In this way the agent acts as an interface between HMI and web service.
- Web service, performing the requested service, supported by ontologies.

With this configuration in mind, flexible data interaction architecture has been developed to provide the best access depending on agents and data repositories available. This means, that, once the operator has requested a specific result, the agent can use mainly two different communication options, as shown in figure 11.6.

- Direct communication with database can be performed if the database fulfils the MIMOSA specification. Then the agent only transmits XML commands to the web service, that in turn accesses the database for data.
- If local database is not MIMOSA compliant, the agent may choose to send the data in XML format.

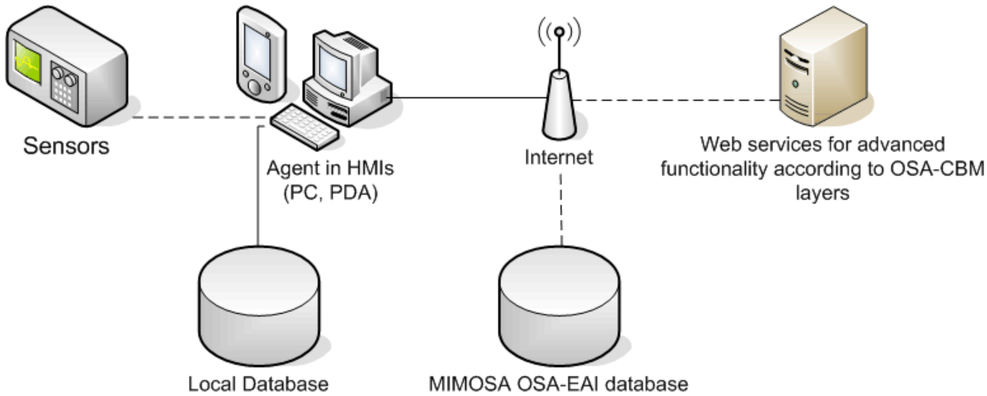

Fig. 11.6 Communication architecture among HMI and web services, through the usage of an agent storing data in MIMOSA database

As an example of this interaction, figure 11.7 depicts a sequence diagram to request a diagnosis service, with direct communication sending data in XML format.

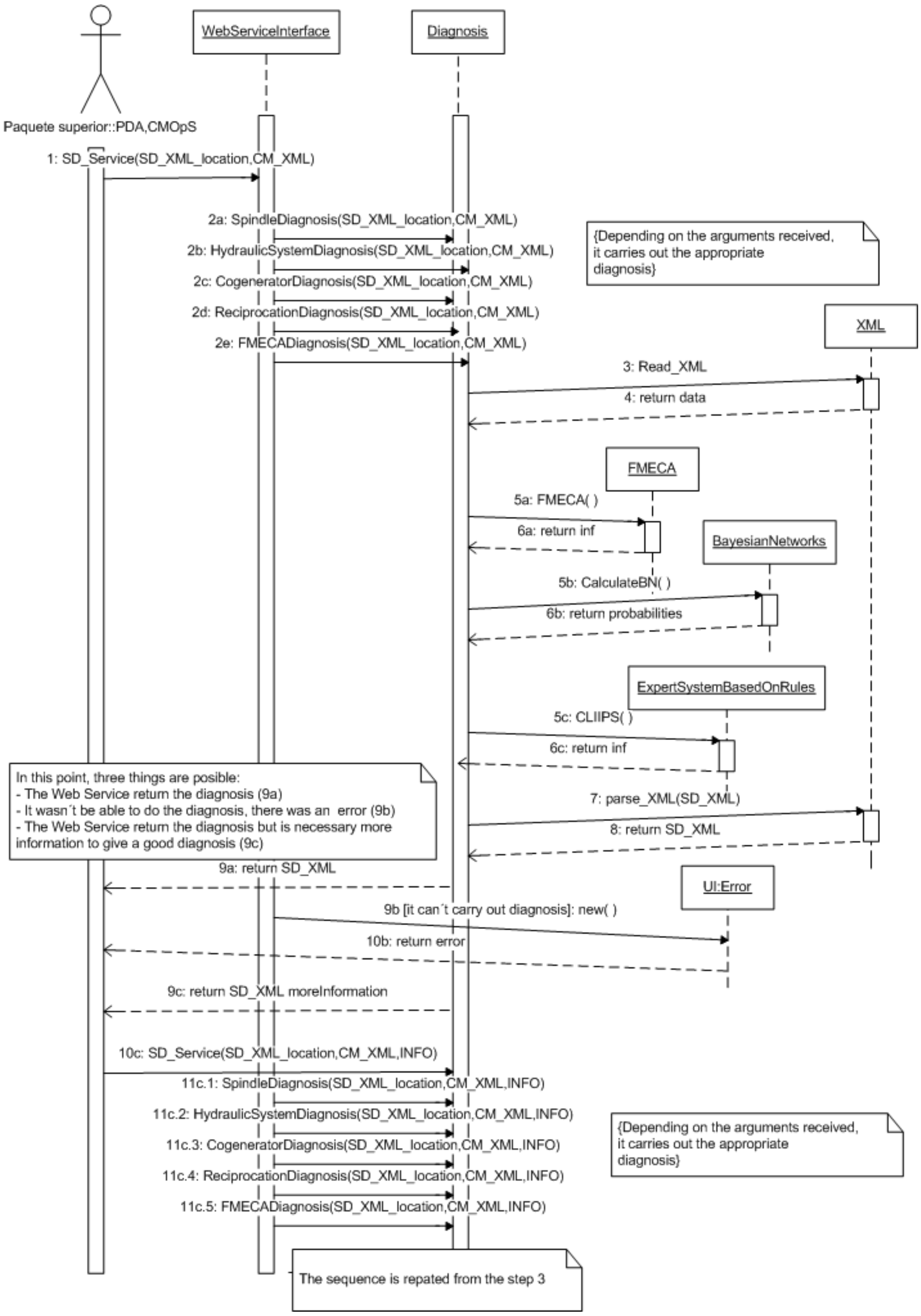

Fig. 11.7 Sequence diagram for diagnosis web service

The performance of every diagnosis function follows next steps:

- acceptance and validation of XML file,
- extraction of data from XML file,
- generate diagnosis alerts with associated probabilities and severities. Depending on component, the service can manage one or more object to issue a heath assessment:
  - a Bayesian Network,
  - a CLIPS expert system: based on rules and
  - FMECA definition,
- parse alerts to XML file,
- return XML file to agent and
- it is necessary to perform a visual inspection or other test, the agent could request in a second step the diagnosis service with added information.

In this example, it is interesting to point out how both mobile PDA and CMOpS actors share same access to web services. Last, this example shows that it is possible to frame existing process systems within CRIS formatted web services, to take advantage of already existing intelligence. For instance, one of the existing diagnosis processes is based on previous developed systems (Gilabert 2006) using Bayesian networks to facilitate a model that can work with uncertainty and can also be adapted with feedback information. In this sense, most web services have been developed using .NET platform as a web application, using Microsoft Visual Studio .NET programming environment, and the database implemented with Microsoft SQL server 2005.

11.3.3 Web service for condition monitoring

One of the web services used for this e-maintenance platform will be devoted to perform condition monitoring tasks. The condition monitor receives data from the sensor modules, the signal processing modules and other condition monitors. Its primary focus is to compare data with expected values. The condition monitor should also be able to generate alerts based on preset operational limits.

The CM web service can analyse scalar data in four different forms:

- scalar values directly surpassing a direct static alert; alerts are defined by fixed limits,
- scalar values that surpass a static alert 'relative' to the original component status; depending in deviation, an alert is issued associated to a specific severity,
- scalar that surpasses dynamic alerts, based on the evolution of last sample values and
- scalar that surpasses a given alert when combined with another parameter.

The CM service will request alert values. In case of not provided, it can also request information concerning the specifics of the component, such as component type, and then look up for information concerning these specifics. In the end, the web service will return the type of alert surpassed and the severity.

11.3.4 Web service for diagnosis based on vibration and oil data

The diagnosis or health assessment receives data from different condition monitors or from heath assessment modules. The primary focus of the health assessment module is to prescribe if the health in the monitored component, sub-system or system has degraded. The health assessment layer should be able to generate diagnosis records and propose fault possibilities. The diagnosis should be based upon trends in the health history, operational status and loading and maintenance history.

The aim of this web service is to identify the type of problem related to an electro mechanical component. It can cope with many different symptoms and faults, which include unbalance, misalignment, gear and bearing related problems, etc. It also includes processing of information specifics of multi-speed machines, such as in manufacturing systems. The web service can receive the following set of alarm types as part of the input configuration, according to measurements of vibration and oil.

The core of this service has been modelled using a probabilistic model called Bayesian Network (BN). A Bayesian network is a model (Díez 2000). It reflects the states of some parts of a world that is being modelled and it describes how those states are related though conditional probabilities. All the possible states of the model represent all the possible worlds that can exist, that is, all the possible ways that the parts or states can be configured.

The representation is a Directed Acyclic Graph (DAG) consisting of nodes, which correspond to random variables and arcs, which in turn correspond to probabilistic dependencies between the variables. A conditional probability distribution is associated with each node and describes the dependency between the node and its parents.

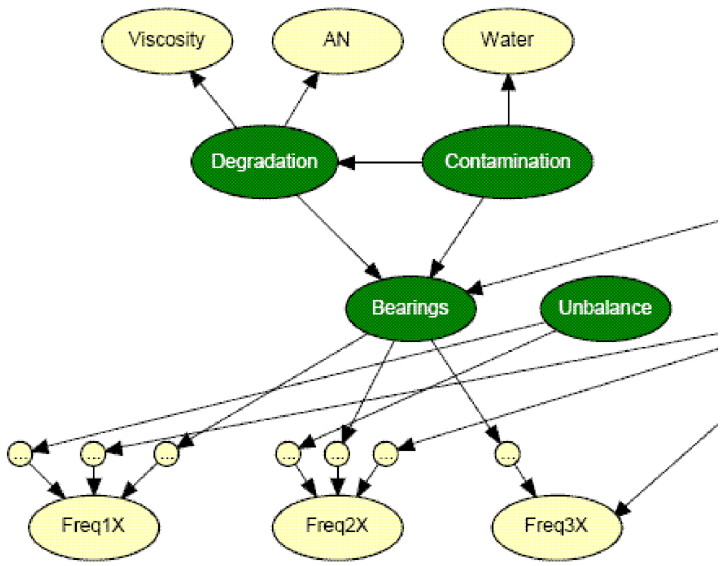

Fig. 11.8 Excerpt of Bayesian network

In the network prototype shown above, the qualitative relationship indicated by the direction of the link arrows corresponds to dependence and independence between events. That is the, nodes higher up in the diagram tend to influence those below rather than, or, at least, more so than the other way around. On the other hand, the quantitative relationships between nodes are defined by conditional probability tables, in case of continuous variables, conditional probability distributions.

Many practical tasks can be reduced to the problem of classification, including Fault diagnosis. A Bayesian network helps tackle the problem of classification in a way that helps to overcome problems that other methods partially address:

- able to mix a-priory knowledge together with data/experimental knowledge,
- explanatory abilities,
- uncertainty management – causality management and
- learning both parametric and structural issues.

One important characteristic of this inference model is the adaptation ability. In this way, introducing risk values of environmental variables and expected parcel risk value, the Bayesian network adapts the weights of conditional probability tables, approximating to desired solution.

The development of the Bayesian network has been done using Hugin Research tool (Andersen 2089). This software has a graphic interface on windows operating system so that Bayesian networks can be designed and it is possible to see probabilities propagation when node instances are set. An important feature is that Bayesian networks can be embedded into custom applications through an API.

11.3.5 Web service for prognosis

Prognosis web service implements functionality to compute the remaining useful life of the component submitted to a degradation mode. The design of the prognosis web service was focused on two specific cases of prognosis: reliability based and condition monitoring based.

The development of this prognostic web service is necessary in order to compute the remaining useful life of the asset or segment. Two type of prognosis has been implemented:

- reliability based prognostic is performed taking into account influence variables through the use of Proportional Hazard Model (Cox 1972) and
- condition based prognosis is performed on an indicator of the health of the asset/segment.

These 2 types of prognosis have been chosen because they correspond to the ones required on the TELMA platform (see chapter 14.3) that will be used for testing purposes. In the end, a unique web service was implemented and the choice between the approaches was performed through the choice of the model used for prognosis. This choice was done in the call to the web service.

Since the communication architecture was performed by means of XML data, an agent was in charge of collecting data from the MIMOSA database and the specific database. The principle of operation was to deliver a client the result of prognosis. To reach this aim, an agent was used in order to collect data and send them to the prognosis web service. Hence, the prognosis web service performs only the prognosis whatever the data could be. The architecture is described in figure 11.9. The use of TCP/IP communication allows to locate the client and the agent on the same PC/PDA or on different PC/PDA. In the case of a PDA client, locating the agent on a PC makes information exchange lighter between PDA and the network. The Internet Protocol (IP) addresses and the port used for communication can be set on the agent.

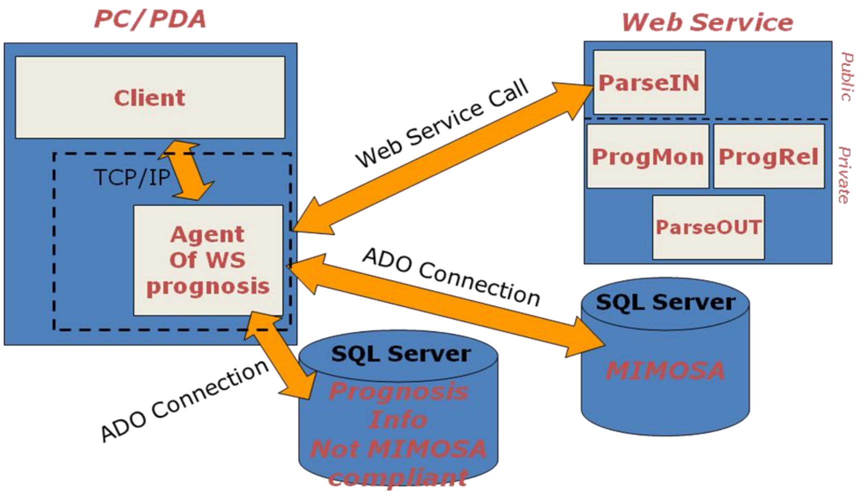

Fig. 11.9 Principle of operation of the prognosis web service

The principle of prognosis is to forecast the future health of the asset/segment using a particular model. The RUL is obtained when the computed health reach an upper or lower limit using data that begin from the last start after a maintenance action that brings back the component/function into an "as good as new" state. At the present time, the two available models for prognosis are the two described below.

11.3.5.1 Proportional hazard model

The proportional hazards model (Cox 1972) assumes that the failure rate (hazard rate) of a segment/asset is the product of:

- an arbitrary and unspecified baseline failure rate, $\lambda_0(t)$, which is a function of time only and
- a positive function $g(X)$, independent of time, which incorporates the effects of a number of covariates such as humidity, temperature, pressure, voltage, etc., included in the X vector.

The failure rate of a unit is then given by:

$$\lambda_0(t)= \lambda_0(t).\ g(X)$$

We implement the exponential Proportional Hazard Model $\lambda_0(t)$ is a constant. $g(X)$ is of the form:

$$g(X)=\exp(\beta.X)$$

where β is a vector of parameter for the covariates.

The use of PHM model for an asset/segment and a hypothetical event is done by defining a model whose type field equals 'PHMexp'. The parameters of the model that have to be defined in the specific database are:

- λ_0: the value has to be specified and
- β: for every β_i associated to a covariate, the value have to be specified and the measurement location corresponding to the covariate.

11.3.5.2 Exponential curve fitting

The exponential curve fitting algorithm is based on the identification of the parameter of an exponential curve to the past values of a degradation/performance indicator. The equation of the exponential curve is:

$$I=K.\exp(\lambda t-t_0)$$

The identification used for the parameter identification is the least square method. The only parameter of this model is the number of points used for the identification. Indeed, it could change since, when the degradation has just been detected only few points are representative and when it occurs “long” time ago, several point shall be used.

11.3.6 Web service for scheduling

The *Advanced Scheduling Module* was realised as a web-service, residing at the decision support layer as defined by the OSA-CBM. The module is expected to utilise data from the prognostics layer (e.g., reliability-based, empirical feature-based, model-based information) and allow for the scheduling of maintenance work orders based upon predicted condition of the equipment, thus helping to streamline the process and reduce maintenance costs.

The key implementation technology for information transport will be XML. In relation to this, the OSA-CBM standard requires the definition of an XML schema, which will define the acceptable structure for the OSA/CBM XML messages.

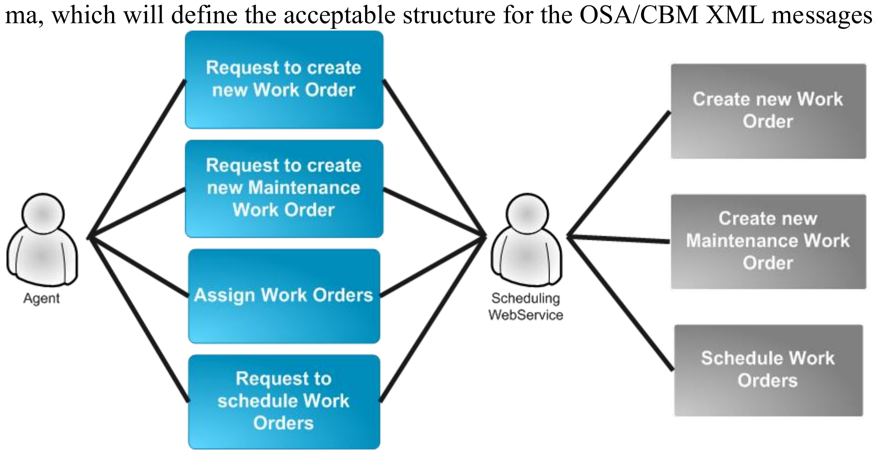

Fig.11 Scheduling work orders modules

According to figure 11.10, the scheduling software module provides a scheduling web services interface, which accepts input data organised in XML format. The *XML handler/parser* is responsible to process the XML input to provide the required scheduling data to the core element of the scheduling software module. In addition, the *scheduling core* subcomponent takes responsibility to invoke the required scheduling algorithm and, along with the available data (as retrieved by the *scheduling database*), provide the produced schedule back to the scheduling web service and its invoker.

11.3.7 Testing web services

Different platforms have been used to test the web services and its advanced functionality:

- TESSnet: tested the web services for data acquisition, data manipulation, condition monitoring and diagnosis and
- TELMA: tested the web services for prognosis and scheduling.

TESSnet software tool (Gilabert 2008) has as main target to detect mechanical problems in lubricated rotating machines in order to save time and money. It is predictive maintenance software based on mainly in oil analysis which performs an automated monitoring and diagnosis. TESSnet is the tool used in this framework to perform different tasks by means of DynaWeb's web services. It is predictive maintenance software based on oil, vibration and temperature analysis which performs an automated condition monitoring, diagnosis, prognosis and decision support.

The platform stores measurements both from on-line and off-line sensors as well as laboratory analysis results. They are stored using a hierarchy of components: company, plant, machine, assembly, sensor and measurement.

This tool has been chosen for validation purposes, that is, to validate some web services over this application. Apart from that, some prognosis and scheduling has been added to the platform.

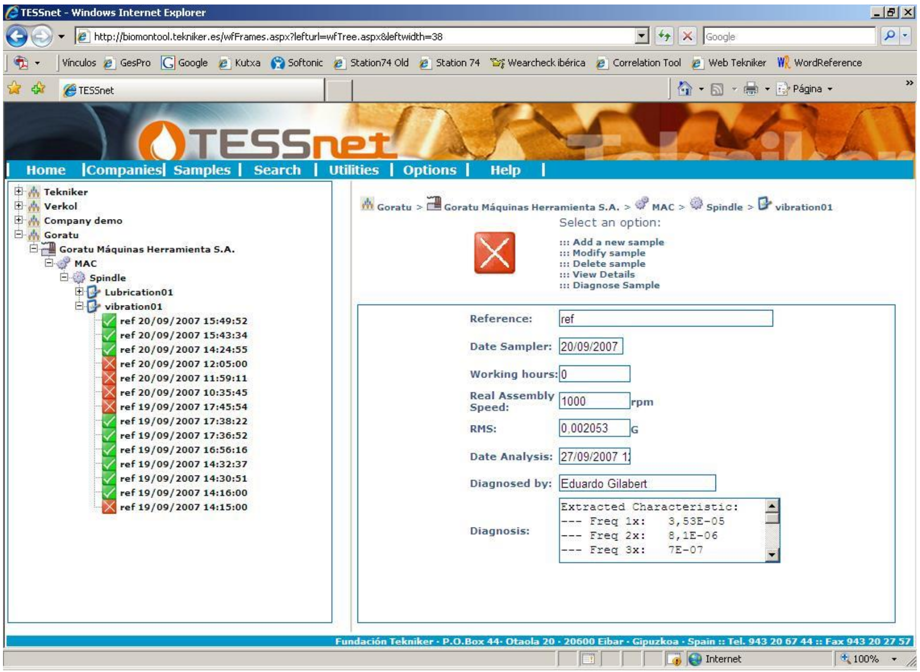

Fig. 11.11 TESSnet screen for vibration measurement

On the other hand, the TELMA platform (Levrat 2007) and has been developed mainly for supporting in relation to e-maintenance:

- the engineering and deployment of CBM and proactive maintenance strategies and
- the assessment of the impacts of these strategies on the performances of a manufacturing system:
  - productivity,
  - quality and

– costs.

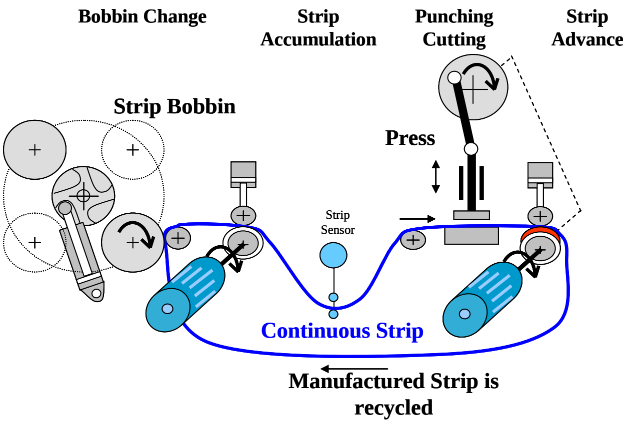

Fig. 11.12 TELMA platform and its physical process: unwinding metal strip

The specifications of the TELMA platform have been defined to answer to a group of teachers and researchers wishing to have at their disposal a training platform in the areas of maintenance, tele-maintenance and e-maintenance.

In that way, the platform is designed for:

- a local use in the frame of conventional training activities,
- a remote use via Internet for operation on industrial e-services (i.e. Tele-monitoring), and (b) for accessing to production data, performance data and
- a use for e-teaching and e-learning as application support of courses in the e-maintenance domains.

11.4 Conclusions

A set of semantic web services have been designed and developed in order to provide advanced functionality related to maintenance tasks. The main concept is to use them as plug-in components in a distributed environment in a company, depending on their needs. For this purpose MIMOSA database has been used as standard which support all communication data. In the end, the set of developed web services constitute a backbone depicting the OSA-CBM layers.

The web services integrated are very different in purpose, as cover from data manipulation layer to decision support. They are also very different in nature. From basic data manipulation concerning vibration signals, to sophisticated diagnostic module for diagnosis on lubricated machinery based on the use of Bayesian network. It is also interesting to point out that different algorithms are present in each layer, so they can be used depending on the needs, or can even collaborate for a global solution at end user. At the end, the web services developed are just an example of what should be at the end in the final product: a big number of methods and web services, at the choice of the user. This will give the real strength to this web services framework.

The end-users' needs has been studied and according to this, the web services functionality has been developed. Moreover previous developed applications as TESSnet and TELMA have been adapted with the same purpose. Afterwards, the web services have been tested and their functionality has been validated, testing that it copes with user requirements. Next activities related to this new approach should be addressed to provide more advanced functionality and better integration between different components which compose the architecture.

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8.4 Economical and technological prospects for e-maintenance

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Resumen

Este artículo ofrece una vista genérica de E-mantenimiento y señala los beneficios y los obstáculos que aún existen en el camino para apoyar el ciclo de vida completo de un producto a través del E-mantenimiento, al tiempo que proporciona una evaluación crítica del estado actual de cosas. Sobre la base de esta discusión, el documento busca evaluar cómo se desarrollará el e-mantenimiento en un plazo de 5-10 años. Se hace hincapié en cómo los usuarios finales pueden beneficiarse del e-mantenimiento.

Economical and technological prospects for e-Maintenance

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Abstract: E-Maintenance has raised increased interest in recent years. During the last years we have seen the development of e-Maintenance techniques. The key elements are the extensive use of Internet that has exploded and rapid development of sensors and processing power**.** It can be claimed that the use of e-Maintenance at the moment still is at infant stage. This paper offers a generic view of e-Maintenance and points out both the benefits as well as the hurdles there still exist on the road to support the complete life cycle of a product with e-Maintenance, while providing a critical assessment of the current state of things. Based on this discussion, the paper seeks to assess how e-Maintenance will develop within the next five to ten years. Special emphasis is given on how the end users can benefit from e-Maintenance i.e. how radical the change really is and what are the financial implications related to its adoption.

Keywords: e-Maintenance, Wireless Technologies, Diagnosis, Data Management, Engineering Asset Management

1. Introduction

E-Maintenance has become more and more popular during the last few years. The reason for this is twofold. The hardware and software that can enable e-Maintenance has developed very quickly and today Internet through wireless networks seems to be available in many places. At the same time the manufacturers of machinery are strategically moving towards developing service business for taking care of the machinery they have produced throughout the entire life cycle of the equipment. In order to be able to do the latter move the manufacturers need tools for taking care of the machinery in a profitable and reliable way and this is where e-Maintenance comes to the picture. E-Maintenance can in its simplest definition be considered a technology where information is provided where it is needed and maintenance is a task that is about information when done in an effective way. In modern maintenance scenarios the actions are carried out at optimal timing before breakage and are based on need not on calendar. In recent years quite a lot of research has taken place covering various aspects of e-Maintenance. In particular, most of the assumptions summarised in these pages are related with ideas, views and results achieved as a consequence of Dynamite (Dynamic Decisions in Maintenance, IP017498), a large European research project where many aspects of the future technologies that will support e-maintenance processes have been tested and validated. Many of this ideas and results are covered in the recently published book E-Maintenance (Holmberg 2010). This paper tries to take this issue a little further and thus in the following paragraphs the future development of some of the key areas of e-Maintenance are discussed and such aspects as smart tags, sensors, signal analysis, hand held computers, use of Internet and data, diagnosis and prognosis and economy of maintenance are covered.

2. RFID technology

The technological basis for RFID (Radio-Frequency Identification) technology has been available for several decades, yet it is only during the last ten years that it has started to make a significant impact on real world applications. Today RFID technology is considered as the most practical way of interlinking physical assets with the information technology infrastructure. Therefore it has been natural to be employed in ICT (Information & Communication Technologies) solutions for engineering asset management and is therefore considered a key constituent element in e-Maintenance. The initial primary use of RFID technology in this context has been for identification purposes. Avoiding the requirement for line-of-sight, it is a more practical choice, compared to barcodes. Beyond identification, RFID tags can locally store limited information, a feature particularly useful for asset management and maintenance. Being the natural link between the physical and the IT world, they have rapidly considered as a key technology that facilitates the computerisation of asset and maintenance management and the integration with ERP (Enterprise Resource Planning) systems. A key benefit for e-Maintenance can be the combination of wireless sensor networks with RFID technology. This enables the integration of asset tracking and identification, with sensing from specific data collection points. The measurements taken are then immediately contextualised, i.e. they are linked to a specific asset, which operates under certain conditions and work load. Coupled with the usage of handheld devices, this level of integration makes the shop floor machinery data ubiquitously available to the networked enterprise authorised users. The technology can also be employed for indirect localisation, thus aiding the delivery of Location Based Services (LBS). Identifying an asset via RFID tags also serves the purpose of linking a specific user to the asset location. Beyond standardisation and initial success stories, RFID technology considerably benefitted from the rapid drop in the costs of both tags and tag readers, making the investment justification more realistic. A more recent trend has seen the integration of RFID tags with sensing technology. This trend is particularly relevant to e-Maintenance, as in the future it will enable the merging of identification and sensing into simpler to install, operate and manage infrastructures. The wider adoption of RFID technologies in e-Maintenance still faces significant hurdles. Costs should be further pushed down. While the physical integration with the IT infrastructure has become possible, software integration remains an issue, especially when it is desirable for RFID-solutions to be linked with existing IT infrastructures. Furthermore, RFIDs are a source of data themselves. The quantity of data generated by the tags can grow dramatically even with modest tag usage within an enterprise. Another key challenge is to ensure reliable operation in a wide range of operating environments. For all the above reasons, an investment in RFID technology does not only need to take into account the acquisition and initial installation costs, but also the costs required to upgrade the organisation’s IT infrastructure. A further promising trend is related to the production of the RFID tags themselves. Increasingly, R&D efforts are pointing towards innovative technologies which will enable organisations to produce their own tags. Furthermore, the possibility to integrate also the sensors themselves in such an RFID printing procedure, makes it likely that the technology will become particularly relevant for maintenance and asset management. Although the state of-the-art is now reaching this level of technological advances, the technology needs to mature further and prove to be reliable and cost efficient in practice. Once this is achieved, one can foresee a much wider usage of RFIDs in e-Maintenance, as organisations will become capable of producing their own tags in response to the dynamic needs of a constantly evolving enterprise.

3. Sensors going wireless

Maintenance engineering often employ condition monitoring and data analysis solutions, as key enablers for implementing condition-based maintenance. The sensor technology itself has reached maturity level in the past but is now seeing a significant upgrade towards smart wireless sensing. From simple wireless sensing nodes to advanced implementations incorporating system-on-a-chip (SOC), smart sensing has moved well beyond the data acquisition functionality. This actually bonds well with the usage of handheld devices, as discussed in the next paragraph. Chiefly, it enables a significant level of data processing to be performed at the lowest possible level, next to the sensing element, taking the burden from the portable device and reducing the data communication requirements to more manageable levels. The key benefit brought by wireless sensing becomes clear when considering that the sensor nodes are now becoming sophisticated computing components with data input and output capabilities which exploit wireless networking protocols, such as WiFi, ZigBee, WirelessHART or industry-grade Bluetooth. From the e-Maintenance perspective, the wireless sensing nodes are becoming smart monitoring agents, capable of performing automated computational and data storing operations (Monostori 2006). The e-Maintenance vision considers that such wireless sensing components can be exploited and integrated in on line maintenance management systems, insofar as the CMMS(Computer Managed Maintenance Systems) software can encapsulate at least part of the domain knowledge that is related to condition monitoring, including wear modelling, failure modes documentation and component life prediction. Within such a framework, wireless sensing networks are likely to become capable of monitoring, modelling but also diagnosing the machinery condition, capturing each machine's individual behaviour, through learning mechanisms. .The great advantage is that such sensing infrastructures can be easily exploited by both back-office staff and systems, but critically also from shop floor staff, who can take advantage of such a powerful toolset to deliver better, more reliable and efficient maintenance services. Through the usage of wireless sensing, it will become also possible to better exploit the mobile actors and workers in the production system, streamlining the generation and delivery of maintenance orders, arising from the ubiquitous knowledge of the actual machinery condition. Indeed, data relevant to equipment maintenance and condition can become transparently available to personnel, via handheld devices, or even via remote servers. The above can be considered as key enablers for the expansion of maintenance services, wherein maintenance providers can be offered in a much more flexible way, enabling even the execution of maintenance audits by a team of mobile technical staff. From a data processing point of view, an important research direction is how to upgrade the flexibility of monitoring systems to capture individual machinery behaviour by incorporating learning and self-awareness elements in the sensing nodes to be installed at the monitored equipment (Emmanouilidis 2010). This can be served by embedded fault and novelty detection mechanisms and more research effort should be directed in making such a prospect feasible and efficient. Following such trends, wireless sensor networks are increasingly installed as practical alternatives to wired sensing elements. Their key advantages are: a) ease of installation & operation b) scalability c) topology flexibility d) built-in redundancy and thus extremely low sensitivity to sensor faulty behaviour. Currently, wireless sensors have benefitted from the sharp drop in memory, CPU an RF components prices. Sensor boards incorporate increasingly powerful 32 bit computing architectures. More work will still be needed towards establishing adequate middleware to support the easy and flexible deployment of wireless sensing solutions. A significant hurdle for the adoption of the new generation of smart wireless sensing in critical applications is related to their limited battery life. It is known that CPU and even more RF operations are energy-costly and need to be carefully controlled. On one side this can be achieved by software-controlled or network protocol-management energy efficient operation. Yet even more promising is the incorporation of energy harvesting properties into the sensor boards. Recent efforts have been directed towards converting the sensor nodes from passively driven components to power-management or even power generating components. A typical example is the EnOcean initiative, aiming initially at the built asset management communities. Of particular concern in wireless condition monitoring is to determine when and what data to transmit. It makes no sense for a wireless sensor to transmit, if it is not asked to do so or if it has nothing interesting to transmit. Therefore, an emerging research direction is related to embedded-software-driven RF operation. Novelty and fault detection mechanisms, embedded in the sensing nodes, are natural mechanisms to trigger data transmission. Apart from battery life, wireless sensing deployment and applicability may suffer if the sensing nodes are not well suited for installation and usage in industrial environment. For example, they may be brittle structures with not sufficient immunity to mishandling and therefore damage. Other problems are related to wireless interference from the environment or by the presence of several other devices (Conant 2006). More ruggedized enclosures can help in this direction.

4. Signal analysis

In order to use the measured condition and process monitoring signals in an optimal way to support the diagnosis and prognosis phases of e-Maintenance sophisticated signal analysis should be used. In principle all the necessary elements would seem to be available. The processing power of processors has increased and some of the sensors already have this capability thus providing raw material for these analyses. However, it would seem e.g. in the light of literature and reviews (Jardine 2006) that, even though quite a lot of research has taken place and a great number of papers about various signal analysis techniques have been published, no really important methods have gained commercial success since the introduction of envelope technique in the middle of eighties for monitoring bearing faults (McFadden 1984). It would seem that in condition monitoring the use of spectrum analysis together with the envelope analysis is the standard procedure today offered by most of the condition monitoring solutions. It can be speculated that the reason for this is the effectiveness of spectrum analysis and the logic behind it which can easily be understood by the technicians carrying out condition monitoring with the aid of portable data collectors. At the same time the fact is that automatic diagnosis has not become popular again even though a lot of research has taken place see e.g. Emmanouilidis and Pistofidis (2010). The use of spectrum data as the sole information for diagnosis means that the end user relies on data in frequency domain. For a human the combination of both data in frequency and time domains is more complicated and there does not exist a simple way of presenting the data in standard format as is the case with spectrum analysis. However, we can expect that in the future since data becomes available from the exploding number of sensors the signal analysis has to be made automatic so that it then supports automatic diagnosis and prognosis. When signal analysis is made automatic and the available processing power increases more sophisticated methods which would not seem easily understandable for humans in two dimensional figure formats can be used. This can be expected to lead to kind of grey or black box solutions i.e. the end user relies on the automatic signal analysis tool either as in the form of hardware or software toolbox. In the future we can expect quite a lot of research in this area and completion of leading roles. One big challenge is the simultaneous use of process signals together with condition monitoring signals. The process signals define the loading and running condition of the machinery and in order to be able to carry out reliable diagnosis based on the condition monitoring signals they have to be linked to certain loading conditions or simulation models that can support the diagnosis. The diagnosis and prognosis are discussed more in detail in one of the following paragraphs. However, the multi-signal analysis and management is a challenge. How to manage the data so that it is available for analysis and that the data from various sources can be integrated and also saved for later use again for supporting the diagnosis and prognosis task. In most cases the data is today saved in hardware specific format even though there exists standardisation attempts like Mimosa which aims for a common definition of data format so that various hardware solutions could support various analysis tools etc. Unfortunately it would seem that Mimosa has not really gained a meaningful position in the market. This is probably since the end users have not been motivated to ask for the hardware providers to support a common platform and the hardware vendors themselves have then considered it better to rely on their own format. This question of data format does not solely involve condition monitoring but is even much bigger issue in such areas as design data of equipment and process data in automation. In those fronts there are much bigger attempts for the creation of standards defining the all the possible components. Again it is somewhat dubious whether this kind of standards will be the answer. A competing solution for the definition the standards provide is the use of semantics and ontology which will be discussed more in detail in one of the following paragraphs.

5. Hand held computers

It is amazing that PDAs and Smart Phones are not used more in the industry today to support the maintenance technician. There are four major reasons for that: 1) The price of PDAs and Smart Phones has been relatively high i.e. in order to cover the whole maintenance staff the investment would be relatively notable. 2) The maintenance staff is not used to use these kinds of devices. 3) The backend systems do not support the use mobile devices for work management. 4) The remarkable financial potential is not understood in the industry due to the lack of well-known success stories. It can be expected that within the near future a remarkable change will take place. Due to the competition between phone manufacturers the price of Smart Phones is quickly going down and is really of highest importance for the manufacturers. At the same time end users quickly adapt the new possibilities Smart Phones are offering i.e. Internet available everywhere and all the time. Use of email on the road together with the use social communication networks becomes extremely popular. People will rely on phones while searching their own and the location of their friends and services such restaurants etc. Basically the result will be that the two main obstacles on the way to rely on mobile hand held devices while taking care of maintenance actions will be quickly removed and actually a lot of pressure will be put on the third obstacle when younger generation will pinpoint e.g. how funny it is to be filling paper forms. As regards to the third and fourth obstacle the trend in manufacturing industry towards providing services for the entire life cycle of their product will pinpoint that the company's CMMS system really has to support the service business and e.g. the view that companies can base their business on historical data which they according their own words have lots of when the quality of those hand filled forms is of the type "Machine is broken", "Fixed the machine". All the above means that there will be a really fast leap in manufacturing companies towards using handheld mobile devices for tasks like: 1) Work order management 2) Communication with service centre 3) Finding the way to the machine to be maintained 4) Reporting work, availability and location. Even though it is easy to predict the trend it is slightly more difficult to predict the form it will take place. Some of the solutions already exist through Internet connection but the problem is that people do not want to work with mammoth system like the ERP packages that have very funny wording for the tasks that end user needs. Probably due to the described feature a great number of light solutions will pop up for various purposes and industrial sectors and a middle wear is needed to take care of integration and data management. Today PDAs are to some extent used to support condition monitoring and especially finding out the status of the machines through process parameters and error codes. The difficult question to answer is how will these tasks in e-Maintenance be emerged to the above described work management tasks. If the PDA is used for diagnosis and prognosis it needs a lot of processing power for signal analysis which is not normally available in smart phones. There are basically two other options here either the signal processing will be taken care by smart sensors which then can provide already processed data to the hand held device or the data can be processed through web services provided by the Internet connection. However this would mean a lot of very low level communication which does not sound very effective. Thus the most probable trend is the rapid development of smart sensors that can support the handheld computers and then when needed the already processed data from various individual sources can be further analysed and integrated through the data fusion capability offered by Web-Services. On the long run technologies like Virtual Reality (VR) and Augmented Reality (AR) can be expected to help in carrying out maintenance work. Today the current manuals are in the form of figures that tell the maintenance technician how to carry out maintenance. With handheld computer video is an option although the drawback is the amount of work needed to produce that kind of material and thus it will probably never cover maintenance tasks widely. Assuming that there exist 3D models of the machinery in question VR technology could be an option to support carrying out maintenance actions. As the term implies AR technology in principle provides additional information to the real world and in maintenance this could be very beneficial especially when the machinery has very complicated structure. Both VR and AR technologies have been tested in research projects. In order to become popular the challenge is the in the production of data i.e. when 3D design models can be automatically used to produce VR and AR material they might become popular since seeing components of machinery to fit into their place like in video is much more easier to understand than a set of figures and consequently a person with lesser education could be expected to manage the maintenance tasks.

6. Internet and data

Nowadays Internet is a real support for business. It is considered as a disruptive technology because their impact in the world, enabling a distributed communication and information storing, in synergy with other communication technologies. The use of Internet for maintenance purposes has been crucial for the e-maintenance concept. Moreover, web services are becoming a fundamental technology for performing e-maintenance. Web services allow the central processes in e-maintenance through the existence of these distributed services in the web to carry out information analysis, management, order execution, even data capture. Computers connected to internet are able to interchange messages using web services, since the HTTP port used by web services are always open, even in the most restrictive firewall configurations. Furthermore, the Semantic Web is a world project that intends to create a universal medium for information exchange by giving meaning (semantics) to the content of documents on the Web, in a manner they are understandable by machines. The Semantic web would provide the required data in real time supported by web services, in a future e-maintenance scenario. Nevertheless, the adoption of this new architecture is a slow process for different reasons. Usually companies have a lot of information in paper format and it is not always easy to make changes in the company culture. Also the adoption of a standard for data format is required, that would support products through their life cycle and the integration of different technologies. The communication among distributed components needs to set a protocol, but the complexity of the data makes the management of data a key issue that should be managed in a centralised way. MIMOSA organisation is dedicated to developing and encouraging the adoption of open information standards for Operations and Maintenance in manufacturing, fleet, and facility environments from the beginning of this decade. MIMOSA provides the standard OSA-CBM (Open Systems Architecture for Condition Based Maintenance), for information acquisition processes, developed to support interoperability through different CBM components. The standard OSA-EAI (Open Systems Architecture for Enterprise Application Integration), also provided by MIMOSA and complementary to OSA-CBM, was created to solve the problem of integrating different applications. In fact, OSA-EAI is a big database containing hundreds of tables. Mimosa definition covers issues related to measurements, condition monitoring, diagnosis, prognosis and management of maintenance work orders. However, the main drawback is the adaption of OSA-EAI in the company, a difficult step since most of times they are not used to work with relational databases. OSA-EAI is well documented and it is easy to download and install to run it is not an easy step to start using a database in a logical way. Actually the installation requires a lot of effort in discussing how OSA-EAI should be used in order it to be an effective tool. But the question is if this is a hopeless route, since it is necessary to understand 100,000 items in a standard simply for definition of concepts. Other added problem is to keep up to date the database. The semantic data has in the end a low level definition which offers many degrees of freedom when users try to understand the database definition. In the end, in order provide interoperability among components and software, more effort has to be done to provide a useful and easy way to interchange data.

7. Diagnosis and prognosis

As explained earlier in this paper the change in maintenance strategy and the increase in the number of sensors and consequently condition monitoring will lead to great need of automatic diagnosis which also means that a huge leap forward has to be taken. It is amazing how poor the status of automatic diagnosis still is in industry e.g. very few reliable solutions are used to support condition monitoring of rotating machinery even though a lot of research has taken place in this field. If studied critically it would seem that in many cases the researchers have not had a wide enough view of the problem they have tried to solve. There are numerous studies about classification using e.g. neural networks and consequently a great number of solutions have been developed which work in the laboratory with the type of date they have been trained with but not in the field see e.g. (Dimla 1997). Even though the article has some age it would seem that the situation is still the same and that the biggest challenge is really to have wide enough view in order to be able to handle sensors, signals analysis, classification and especially wear development in order to be able to produce something that is really beneficial. It would really seem that many researchers are very naive when they assume that a clever classifier can solve the problem. In fact we can claim that if the use of right kind of sensors with proper signal analysis techniques are overlooked there is no change of success since if the basic information the classification relies on is of poor quality and meaningless there is no way a good classifier could solve this problem and really be of help. Since a number of companies are moving towards providing services for the machinery they manufacture much data will become available to support the condition monitoring task. Through this development especially the improved understanding of wear models of the machinery components will help in the automation of diagnosis. Also it can be expected that more process data will be available and in connection to that simulation models will be available and thus provide additional information to support diagnosis and prognosis. When the development of signal analysis techniques as described earlier in this paper is taken into account the automatic diagnosis of the condition of machinery components can be expected to take a big step forward and really become available for many kinds of components. Furthermore the prognosis failure development of many kind of components suffering from wear as a function of loading will become possible on a level that helps the introduction of CBM. Due to the complexity of diagnosis and prognosis of rotating machinery the data mining and classification techniques as such do not really give a lot of support but they will be very beneficial in handling spare parts and reserving resources based on more statistical than physical modelling. It can be expected that the ordering of spare parts and their management will actually become semiautomatic. It is natural to start from the less expensive parts that are used in numbers and then eventually go to the more expensive and rare parts in case of which a human checking process will probably be used for quite a long time in the future. As such modern e-Maintenance solutions could already today carry out all the ordering and work force management automatically but scenario of things going wrong i.e. sending out wrong orders for parts and works in great numbers is prohibiting this development. However, this process will naturally go further as more experience is gained from the semiautomatic solutions.

8. Economics

Today maintenance is still considered in most cases as a cost centre than as a business opportunity, as it is not straightforward to quantify the value that advanced maintenance strategies may add to existing operation processes, nor to the overall business model of a company. However, maintenance business is moving forward when companies understand that maintenance processes have more margins for optimization than operation. There are many indicators that adopt multiple variants in order to satisfy specific requirements (EN-15341 Maintenance – Maintenance Key Performance Indicators, 2007**)** and financial indicators considering the return of investments (e.g. ROI: Return on Inversion, RONA: Return on Net Assets, OEE. Overall Equipment Effectiveness) can also be a good starting point to understand the three main areas of plant productivity: Availability, Quality and Craft effectiveness. Even though reliability and availability have improved substantially in most companies, the cost efficiency in performing the maintenance operations is still high. An indicator related to this efficiency is 'Wrench Time'. This indicator appears as part of overall craft effectiveness (Peters 2003) and represents the percentage of time an employee spends applying physical effort or attention to a tool, equipment, or materials in the accomplishment of assigned work. It is used to determine how efficient the plant is at planning, scheduling and executing work. According to (Wireman 2003) a typical wrench time in many organizations in EEUU is of 35%. Another market demand is related to an increasing number of companies which acknowledges maintenance as a natural way to extend operation and productive processes, and are thus looking for the opportunity of moving towards service business. This may generate important benefits to the first companies reaching a competitive service, and make them less vulnerable of the market changes. At the end, there is a shift towards maintenance activities where the main business objective is more related towards keeping the needs of the customers satisfied (by guaranteeing the productive assets on the right time and right status) than just increasing the number and quality of assets being produced. This trend towards 'services' is also part of another trend towards more sustainable business models, with environmental aspects in particular becoming economically significant. This new model implies also less costs concerning raw materials, energy expenditures and recycling needs as indicated in (Takata 2004). Current worldwide technological progress can be traced back to a few concepts that have resulted disruptive, due to their impact, two of these technologies can be tagged as 'internet' and 'micro-technologies'. First, the use of miniaturized devices is expanding and reducing costs with respect to data capture and acquisition, as in new sensor devices (Aranzabe 2004). Moreover, the impact of miniaturized devices in data communication and storage is even higher, starting from mobile devices and their versatility today, to wireless communication options. Second, Internet is the standard vehicle for communication, as well as for distributed storage of data and information. The synergy with communication devices is really crucial for the raising of e-business and the main driver for e-maintenance (Muller 2008). These two technologies are revolutionizing the world, from business and politics to leisure and social attitudes, but they have not yet impacted as much in the maintenance scenario. The coming of these technologies is not far has the market drivers are seeking for their incorporation, and e-maintenance provides the framework for transforming technologies into concrete utilities for advanced services business models. This new model implies also less cost concerning raw materials, energy expenditures and recycling needs. The trend in cost reduction for ICT technologies shows a steady decrease that enables today their use in an increasing number of scenarios. This is also in line with reduction detected in price of commodities (Cashin 2002). This has, as a consequence, the appearance of multiple products that facilitate capture, transmission and analysis of data and information in fast, distributed and economic ways. This is also true with respect to e-maintenance, many ICTs, specially related with predictive and condition based strategies as well with maintenance execution (e.g. virtual and augmented reality). Moreover, new standards have appeared that facilitates a way to understand how different technologies may interoperate (Thurston 2001). All this new technology surrounding everyday maintenance & operations activities is having severe implications in the way operators may do their work, not fully grasped yet. For instance, due to the rapid development of smart phones it is likely that average operation & maintenance staff will be easily equipped with a device capable of many different tasks – not just maintenance. Also, a certain amount of e-Maintenance will be introduced by force (i.e. when people use smart phones at home and spare time and have all information available whenever they want it). Many studies (Aranzabe et al (2004)) show that it is beneficial to move to e-Maintenance and CBM where even small steps can be economically justified. It is also possible to list a number of positive impacts that can be clearly addressed. First of all, it is known that change from corrective to predictive maintenance strategies allows the reduction of breakdown suddenly causing production stoppages and an increase in availability. Whereas condition monitoring systems have traditionally focused their benefit on increased safety corresponding to detecting failures before the planned time-based schedule and thus minimizing the risk for sudden breakdowns, condition based strategies can also increase availability by extending the maintenance intervals, sometimes far beyond actual maintenance schedules. With respect to efficiency and craft effectiveness, the use of RFID systems together with advanced CMMS systems will allow that right maintenance technicians with right tools and skills to address work orders. Also, automatic diagnosis and prognosis of the condition of machinery allows that Maintenance actions are optimized in view of equalized maintenance. This is not just the lifetime extension due to the control of the condition of the asset, but also to decide optimum maintenance period to resources and expected operation (equalized maintenance, operational reliability). Concerning current condition based maintenance activities, the use of novel and cheap sensors and communication systems allows the substitution of off-line manual systems by on-line automated inspection mechanisms, where there may be a reduction in organizational costs (e.g. third party subcontracting, training own personnel) related to the extraction, conditioning and analysis of information related to manual inspections. This is important in many cases, as the cost of manual inspections, together with certain failures and delays in data transmission (bad labelling, improper data extraction, etc.) make it difficult to maintain high sampling frequencies, which in some cases make PdM (Predictive Maintenance) barely efficient. As the main potential of predictive maintenance is the ability to react on time, on-line inspections generate less risk (in terms of evolution of the fault indicators, in anticipation, etc.) and enable more time to schedule maintenance execution. At the end, one of the most important challenges is to observe how these e-maintenance technologies can help best organizations to exceed 50% of wrench time, by reducing human-centred activities (unscheduled corrective, time-based preventive, manual inspections…). Important Quality and safety improvements may also be expected. Reduction of sudden breakdowns of machines, especially having high power and speed have a high risk of causing accidents and this can be avoided. This reduction also affects to unplanned quick repair activities, where improvised equipment carried out without proper knowledge increases the risk of accidents. RFID again may play an important role in safety. These systems together with appropriate smart devices facilitate that right machine and machine component is addressed with maintenance actions, together with spare parts and adequate craft instruments necessary to execute the maintenance action. Virtual reality and augmented reality tools also provide guidance on maintenance execution, reducing both time to execution and risk of improper maintenance execution, increasing maintenance quality, and hence, reliability and safety of the asset and maintenance process. Even though the future for e-maintenance is clear, new investment in maintenance or service businesses should normally be supported in something more than assumptions, especially if they have an evident initial cost. However, it is really challenging to assess the benefit of e-maintenance systems today. In cases where the business model changes (from product to service) there are no reference points to understand the benefits e-maintenance may bring. In most of the cases a direct benchmarking with competitors or third companies that implementing similar solutions are partial and/or biased. In many companies, especially SMEs, the main idea is to 'start from scratch'. However, this is also difficult if there is not a quantitative idea of the initial status nor of the future advances, In these cases, a necessary step is to tailor the necessary Key performance indicators (KPIs) to company characteristics and to follow their evolution. In fact, most companies need also to include KPIs (existing anyway as part of standardization efforts in both Europe and America) in order to understand the gains related to availability, quality and craft effectiveness that may be worthwhile. Main KPI in existing companies appear to be related to product reliability or availability, which is short sighted with respect to direct maintenance costs, the true battle horse where e-Maintenance may show their benefits. Once KPIs are clear, it is necessary to determine a coherent method to analyse what are the most important aspects to improve concerning the e-maintenance economics. These analyses (cost-benefit, cost–effectiveness approaches) are starting to appear as strategic tools that allow incorporating predictive strategies. Even though e-Business processes are mostly indicated as ‘revolutionary’ tools, it is also possible to ‘evolve’ from existing scenarios. In these cases, it is important to detect the most critical or negative processes assets or performance indicators that are really affecting cost-effectiveness (e.g. with the aid of design reliability tools). Once performed, it is possible to examine and evaluate technologies that can improve existing strategies with a clear cost-benefit analysis. With an introspective analysis of the company economics, it is possible to achieve high benefits from the incorporation of e-maintenance technologies, starting from those oriented to predictive strategies.

9. Conclusion

During the last years we have seen the development of e-Maintenance techniques. The key elements are the extensive use of Internet that has exploded and rapid development of sensors and processing power. It can be claimed that the use of e-Maintenance at the moment still is at infant stage but especially motivated by the changes of strategy of manufacturing industries towards the capability of proving services throughout the life time of the equipment they have manufactured will introduce a great leap in this technology. This step forward will be supported and strengthened by the hardware development but the most important factor is the availability and usability of new data that can support diagnosis and prognosis and help to raise them to a level that is of real benefit for the maintenance technicians. The development of new signal analysis techniques combined with simulation models can be the factor that really means a breakthrough in prognosis of the life time of components of machinery and consequently real proactive condition based maintenance will be enabled. Many of the technologies are available already now and their introduction could be easily justified economically but naturally there is some sand in the wheels i.e. it will take some time prior all the available options will be taken into use but naturally the success stories of those in the forefront will encourage the adaption of new technologies in greater numbers.

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8.5 E-Maintenance and Decision Making in Maintenance

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Resumen

Este capítulo de libro justifica el uso de E-mantenimiento no solo en relación con las nuevas tecnologías utilizadas, sino además con los nuevos servicios esperados, lo que lleva a dar un primer paso en la revolución del mantenimiento, basado principalmente en las capacidades de movilidad. Muestra diversas plataformas de E-mantenimiento para resaltar aplicaciones concretas en la industria.

E-Maintenance

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1 Introduction

E-maintenance is emerging from the major changes in maintenance goal needed for supporting the new sustainable and eco-efficiency paradigms. Indeed traditionally the scope of maintenance activities has been limited to the production vs. operation phase. But as the paradigm of manufacturing shift towards realizing a sustainable society, the role of maintenance has to change to take into account a life-cycle management oriented approach (Takata, *et al.*, 2004) for enhancing the eco-efficiency of the product life. In that way, maintenance has to be considered not only in production vs. operation phase but also in product design, product disassembly, and product recycling … (Van Houten, *et al.,* 1998).
Moreover the product can now play a major role in maintenance mainly when the product is "active" (i.e. Intelligent Product, Holon…) i.e. able to support a part of its knowledge.
These two paradigms of "Eco-efficiency" and "active Product" confer the maintenance a major role, in the future, as a STRATEGIC TOOL for reducing quality defects, increasing production capacity and throughput, improving overall plant productivity and profitability … and for providing the product to the customer at the quality he wants at the price he wants to pay, with the services he expects… for a long time. In this sense, the concept of "life cycle maintenance" (Takata , *et al.*, 2004) emerged to stress this new role leading to develop a general maintenance value chain to keep the functional level of a product - preserving all its characteristics including environmental impact, and to be in line with the business and profit objectives (strategic decision rules)
This new way of thinking maintenance is fully consistent with the system engineering one (INCOSE[1] initiative) in which Maintenance is considered as the main process of the "support system" contributing to the "system-of-interest" (Figure 11.1). Thus E-maintenance is "scientifically and technologically" another thing that a mosaic of models, technologies and standards. It has to be considered as a "System" and the development and integration of such systems (as systems-of-systems) needs numerous Interoperations with other systems and objects.
The main part of these interoperations materializes the link within the value chain between each phase of the product life cycle, leading for each phase, to assign a (sub) objective to be fulfilled (in consistence with the context phases). Each objective and sub-objective is supported by Business Processes (services). If all the sub-objectives (local objectives) are carried out, the global value chain is running well. This system view highlights that a not controlled deterioration of one of the product characteristics in a life cycle phase P can have important impact on the use of the product or on its expected service in the life cycle phase P+1 (after P). Consequently, the conventional strategies (Wang, 2002) such as scheduled preventive maintenance strategies carried out some time too late in relation to the current status of the potential failure are not easily compatible with this maintenance vision. A failure can lead to **a bad product or a bad service delivered by the product**. Therefore degradation-based anticipation strategy (the pro-activity in maintenance) becomes essential,

[1] http://www.incose.org

at this stage, to avoid failing situation with negative impact on product condition (zero breakdown maintenance).
Condition Based Maintenance (CBM) is a practice illustrating at first this type of such strategy and concerns with making decisions and performing necessary maintenance tasks based on the detection and monitoring of selected equipment parameters, the interpretation of readings, the reporting of deterioration, and the vital warnings of impending failure. This strategy supports **dynamics** in the decision.
Therefore CBM is the first step toward a full pro-activity leading to the emergence of E-maintenance philosophy (Iung and al., 2009) for supporting the moving from "fail and fix" maintenance practices to "**predict and prevent**" strategies (Lee, *et al.*, 2006)… while keeping Maintenance as an Enterprise process (holistic approach) - **Integration concept** (i.e. IEC/ISO 62264) for optimizing performances. E-maintenance is a sub-concept of e-manufacturing and e-business for supporting next generation manufacturing practices (NGMS).
A general definition for E-maintenance should be "maintenance management concept whereby assets are monitored and managed over the Internet"[2].
In that way, E-maintenance is integrating the principles already implemented by Tele-maintenance, which are added to the web-services and collaboration vs. synchronization principles (Iung, 2003) to support pro-activity. Collaboration vs. synchronization allows not only to share and exchange data and information but also knowledge and (e)-intelligence and this between all the actors (human, units, department…) all along the product life cycle.

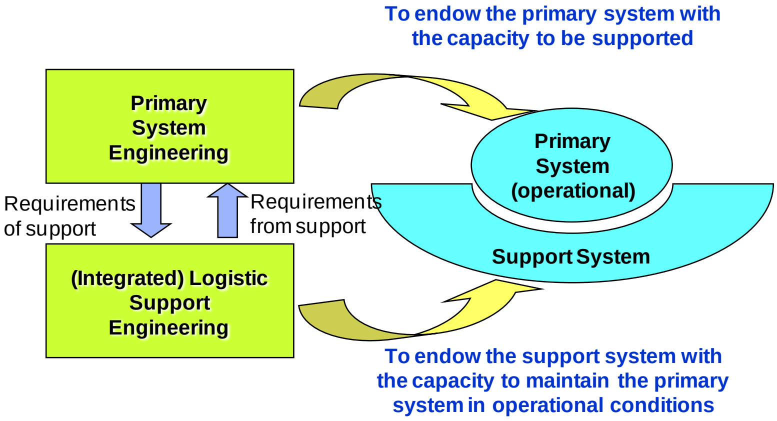

Figure 11.1. Systems-of-Interest and Support System

Indeed the collaboration can be made inside a phase or outside a phase for supporting business process integration along the entire product life cycle (Macchi et al, 2006). It implies to use new technologies such as Information and Communication Technology (ICT) for restoring the flows (e.g. Informational) needed for integration. These new technologies support the implementation of e-Maintenance philosophy as an emergent support for collaboration and pro-activity. Through the "e" of e-Maintenance, the pertinent Data - Information - Knowledge - Intelligence (D/I/K/I acronym) becomes available and usable at the right place, at the right time for taking the best (anticipated) maintenance decision.

Thus the "e" led to consider the e-Maintenance emergence as linked with two main factors

- The appearance of e-technologies allowing the increase of maintenance efficiency to optimize maintenance related workflow (i.e. infotronics technologies). E-Maintenance support is globally made-up with Intra-Net, Extra-Net and Inter-Net parts. These parts are built from a lot of different e-technologies such as Web technology, new sensors, wireless communications, mobile components (e.g. Personal Digital Assistant - PDA) (Arnaiz *et al*. 2006).

[2] http://www.mt-online.com/articles/1201_mimosa.cfm

- The need to integrate business performance, which imposes to the maintenance area the following requirements: openness, integration and collaboration with the others SERVICES of the e-enterprise (new way of thinking maintenance). It leads to consider the e-Maintenance value chain composed not only with conventional maintenance processes (which are not up-graded because reused in the same way for e-Maintenance) and upgraded conventional maintenance processes (from CMMS to e-CMMS, from documentation to e-documentation) but also new processes (new services) which are emerging from e-Maintenance requirements such as business process of prognosis degradation (Muller *et al.*, 2008b) or opportunistic maintenance (Levrat *et al.* 2008a).

Discussion about the emergence of e-maintenance and its fundamental principles can be already found in the e-maintenance special issue (Iung and Crespo-Marquez, 2006), in the books "Handbook of Maintenance Management and Engineering" (Ben-Daya *et al.*, 2009), "e-maintenance" (Holmberg *et al.*, 2010), in some surveys such as (Muller *et al.*, 2008a), (Levrat *et al.*, 2008b), (Iung *et al.*, 2009) ...

2 E-maintenance services

The e-maintenance vision is necessary supported by a lot of **business processes** (the maintenance services) considered as the key elements of the value chain[3] related to the creation of the value for the customer. Indeed an e-maintenance business process is a value chain providing an e-maintenance asset or service to an internal or external client of the enterprise. A business process is generally triggered when it receives an incoming message. It then runs until production of an outgoing message or a flow whose destination is the client of this business process. An e-maintenance business process enables description of what an enterprise does for supporting its e-maintenance strategic decision rule. It is essentially described by flow exchanges between the various activities of the enterprise. An activity is a step in a business process.
As the global e-maintenance value chain supports one phase of the product life cycle (design, production...) or several phases, the business process can be described by lot activities potentially business "distributed": it is generally of horizontal type.
The e-maintenance business processes can be qualified as:

- Operational Processes (set of activities which are addressing the concrete actions of the maintenance operators on site).
- Informational Processes (which are linked to the use and capitalisation of the technical data and information needed for developing operational processes).
- Decisional Processes (which are related to decision-making on action date and time).

These e-maintenance business processes (services) must be materialised by:

- Conventional maintenance processes which are not upgraded because reused in the same way for e-maintenance (no difference between their use in maintenance or in e-maintenance such "operational actions").
- Conventional maintenance process which are upgraded or modified to take profit of the advantages linked to the e of e-maintenance.
- New business processes which are emerging from e-maintenance requirements such as Business processes based on mobility concept or on degradation monitoring.

<u>Examples of updated conventional maintenance services</u>:

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[3] The value chain is described by a sequence of transformation activities

- e-CMMS (full Web) with following functionalities
  - ❖ Automatic data acquisition, Asset Management
  - ❖ Integration with ERP, MES
  - ❖ Workflow
  - ❖ Use of Mobile Technologies
  - ❖ 3-Tier Architecture
  - ❖ ASP Method "Application Service Provider/Providing"
- e-documentation
  - ❖ CMS : Content Management System
  - ❖ DMS : Document Management System
- e-learning (i.e. Ganesha)
- e-test
- e-operation …

Examples of new e-maintenance services:

- Pronostic (Muller *et al.,* 2008b) (Jardine *et al.*, 2006) (see chapter 2 & 4),
- Degradation-based advanced diagnostic (Venkatsubramanian, 2005) (see chapter 6),
- Mobile condition-monitoring,
- Dynamic decision-making in maintenance (Levrat *et al.,* 2008a) (see chapter 8)...

The chain of the processes (and their activities) is based on a business semantics which requires necessarily a semantic interoperability or ontology in e-maintenance. The activities can operate on data, information and/or knowledge even on intelligence (D/I/K/I). The activities are formalised by traditional or more advanced techniques to be executed.
Each business process (and activity) carries out e-maintenance operational objectives[4] which are controllable by performances indicators (performance evaluation), allowing to modify these objectives for e-maintenance continuous improvement (Parida, 2006). Indeed Business Process description is the first issue before any efficient study of performance improvement can be achieved. Performance of an employee, activity or operation … cannot be known until its contribution to the business process and customer value chains is precisely understood.
At this stage, the business processes (and their activities) are not constrained by a **particular organisational approach**. All the business processes forms the conceptual **Map** of e-maintenance business processes (linked to the other Enterprise business processes needed to support integration for establishing systems-of-systems).

3 E-maintenance organization: How the maintenance business processes are organized?

E-maintenance organization supports the phase where jointly the Operational Manager and the IT Manager establish the relationship between the e-maintenance Business processes and their operational mapping within the e-maintenance infrastructure (platform). It consists in projecting the business processes (but especially the associated activities) onto one or more organisations of e-maintenance and then to assess the organizations according to the expected finalities related to the strategic and business levels.

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[4] An objective is a goal that a company/organization wants to achieve, or is the target set by a business process or an operation. An objective allows to highlight the features in a business process that require improvement. An objective can be quantitative (directly measurable) or qualitative

Defining an organisation consists of assigning activities (and its related procedures[5] and operations) to the org-units[6] that will perform these activities on a specific site (Figure 11.2). A site could be internal or external with the company (in relation to the life cycle phase supported) and can prejudge a subcontracting of competences. A procedure describes how the enterprise is organized to carry out the operations necessary for its functioning. It is described by the sequence of operations carried out by the org-units of the enterprise. Performance of each of the procedures can be optimized by use of tools enabling evaluation of their duration and quantification of the resources required for their execution.
From a dynamic point of view, the organisational execution of Business Processes (by means of procedures vs. operations execution) can be done through an "organisational" workflow (An e-maintenance flowchart) which is characterised at least by: the beginning and end of the workflow, the procedures then the operations to be achieved during the workflow development, the algorithms required for procedure vs. operation sequencing, the org-unit interacting with the operations, the informational flows exchanged with the org-units... Only the resource allocation to the operations is not done at this organisational stage because it depends of the IT techniques chosen for leading to a technical workflow (i.e. applications, databases and other resources used by the procedures operations).

During the development of this organisation and more precisely the procedure and operation definitions (and locations), it is necessary to distinguish:

- The procedures (and/or operations) directly linked to the e-maintenance business processes implementation. It will be quite impossible to call them into question unless the Enterprise does not change its e-maintenance strategic vision.
- The procedures (and/or operations) directly linked to organisation choices. Indeed for a specific organisation, if some "business" operations of a same e-maintenance activity (or procedure) are distributed among different org-units, located on different sites, it will require to create new operations in order to re-establish the right behaviour of each operation. Even if the operations are distributed, they have to operate as a whole for supporting the expected (activity) finality. These new operations related to distribution criteria must carry out communication, storage, collaboration, negotiation… For another organisation (less distributed), these new operations will be different (or deleted).

[5] A procedure describes the method of implementing all or part of the business process required to make a product or handle a flow. A procedure is represented by a sequence of operations triggered by the receipt of a message. An operation is a step in a procedure, executed by an org-unit within the context of an activity.
[6] An org-unit represents a person or group of persons participating in the business processes or information system of the enterprise. An org-unit can be internal or external to the enterprise. An org-unit can send and receive messages. It is located on a site; it can intervene in a business process or a procedure. It can draw on resources to handle an activity. It accesses databases to carry out operations using an application. It can be specialized.

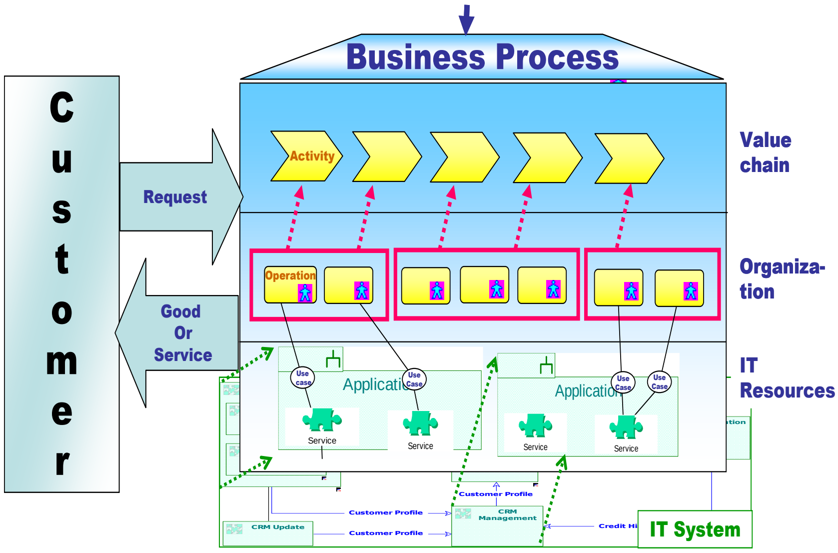

Figure 11.2. From business processes to IT

… But what are the organisations the most adapted for supporting e-maintenance?
In general, the industrial organisation types can be classified in relation to the metric EICM "Enterprise Integration Capability Model" (Hollocks *et al.*, 1997) in order to propose 5 levels for organisation characterisation (evolution, from level 2 of a conventional hierarchy based on coordination, towards level 5 for a flat organisation based on self-organisation supporting criteria such as agility, adaptability). For example, the IMS[7] (Intelligent Manufacturing System) paradigm (Yoshikawa, 1995) is trying to replace the hierarchical structure by an heterarchical or intelligent (hierarchical/heterarchical) one. It breaks off with the well-established Cartesian approach, and advances a new behaviour-based modelling strategy stating that the system behaviour emerges through the dynamics of the interactions of basic manufacturing agents within the manufacturing environment.
The new way of thinking maintenance is fully consistent with this IMS view (i.e. knowledge-based interactions in different life cycle product phases, for different org-units, at different locations…) leading to consider that the organisation most adapted for the e-maintenance (fulfilling pro-activity) is rather located at the level 4 even 5 than at the classical levels 1-2-3. Level 4 materialises a distributed vs. cooperative organisation (from conventional maintenance to more distributed vs. cooperative maintenance).

In that way:

- Collaboration is distinguished from cooperation considering the work as accomplished by the division of tasks among actors (human/automated), and as an activity where each actor is responsible for a portion of the problem solving…, whereas collaboration involves the mutual engagement of actors (human/automated) in a coordinated effort to solve the problem together (Roschelle and Teasley, 1995). Systems that aim at collaborating with other agents in a joint task, necessarily also exploit some cooperation principles as part of their knowledge of how to collaborate successfully, although cooperation need not go beyond the level of action coordination (Jokinen *et al.*, 2000).
- Distributed[8] in terms such as "distributed system", originally referred to computer networks where individual computers were physically distributed within some geographical area. This term in e-maintenance area could be referred to autonomous actors (the automated ones are running on a computer, a PLC, a sensor, a PDA etc.) which interact with each other by message passing (and by developing a cooperation vs. collaboration). Alternatively, each actor may have its own capacities with

[7] http://www.ims.org
[8] Wikipedia definition

individual needs, and the purpose of the distributed system is to cooperate-collaborate the use of shared resources or provide communication services to the actors.

4 E-maintenance scenarios and technologies

The design of a new type of organization (such as previously proposed), more flexible, is supported by the assumption of the existence numerous companies that can benefit from a subset of the technologies readily available today, providing customized plug and play to the desired upgrades with respect to each company's existing maintenance activities. It is also understood that there is not a single 'upgrade' solution that fits for all concerning the maintenance needs.

In a recently finished research project[9], one of the first activities performed has been the study of the use cases that may be involved concerning the upgrade of current maintenance functions related to the manufacturing field, with the aim to facilitate the identification of likely enhancements to actual maintenance processes. Scenarios were extracted out of initial use cases, as likely representative examples of a wider group of companies having similar objectives in the maintenance process, sharing similar technology status, or sharing a need with respect to maintenance technologies needed. As a result, different scenarios were separated, from large companies with de-centralized production systems, OEM suppliers, small companies with few dozens of machining systems and third party consultants.

The table 11.1. was compiled from this end user analysis during the first stages of the project, and clearly shows that the initial assumption is true, and it is not possible to find a single system for a global upgrade of existing maintenance systems. Existing strategies, legacy systems and other issues differ very much, as well as perceived technical problems and economical motivations. The table 11.1. tries to generalize scenarios that can go beyond a particular use case, thus providing an entry point to the technologies for companies that share similarities with one of the scenarios (roles, operational contexts, applications, components, preferred upgrades etc).

Table 11.1 **Summary of end-user scenarios in DYNAMITE project (Arnaiz *et al.* 2007)**

Providers	**Plant operators**	**OEM manufacturers**	**Consulting**	**Transport (OEM + consulting.)**
Context	Single location (Manufacturing plant). Multiple machines	Technical Assistance Services. Guarantees. Multiple locations	Specialized services (e.g. lube analysis) for multiple locations	Specific machinery on movement
Application (Components)	Milling, drilling and high speed machine tools (Hydraulic systems, gearbox, spindle)			Motors (Marine, Automotive)
Current strategy	New PM (10- 20% CBM)	BDM	PM	-
Current economic motivations	Overall economic impact to the company for different	Uneven workload. Enforce remote maintenance procedures on	Decrease downtime, repair and maintenance	Plan new cost –effective e-Maintenance for new

[9] DYNAMITE reference

	maintenance strategies not always known	guaranteed machinery	costs	equipment
Current technical problem(s)	Evaluation of machine condition depending on expert knowledge (subjective)	Improve diagnosis Communication sensors to OEM (bypass CNC)	Lack of experienced diagnosis and decisions over existing parameters	Lack of proper knowledge
Interesting technologies	Include advanced sensors Wireless communication Smart PDAs Include cost-effectiveness	Upgrade to CBM Use remote monitoring e-Maintenance. Wireless gateways Cost effectiveness	Use e-Maintenance to remotely assess expert and communicate to operators. Training systems.	Initiate predictive maintenance
Likely CBM/PM parameters (sensors)	Temperature, Voltage, Current, Oil level, Oil quality, vibration, pressure, Wear debris			

4.1 What are the new technologies for developing these types of organizations

Current results achieved at different research projects (here pending references of PROMISE, TATEM, DYNAMITE,…) have allowed observing several 'new' technologies that can be available for maintenance strategies optimization. These technologies range from hardware devices (mobile systems, sensorics, wireless communications) to new ICT tools that power the e-maintenance concept. In a world where effectiveness demands are always increasing, and several cost (micro-technologies, communications…) are decreasing, many of the technologies outlined can be considered as cost-effective today for many applications.

However, the application of such technologies is, in many cases, not taken into account as there are few ways to assess all costs and benefits that may be linked to the product life-cycle optimization, or to the plant O&M processes. Also, the impact on the organizational aspects is, in many cases, not considered. This is true in all areas, but specially in SMEs where it is not possible to perform extensive studies of the cost-effectiveness gain before implementing new strategies or technologies (e.g. new sensors, changes to PdM, …)

This section shows a series of technologies that may be worthwhile considering in a broad range of maintenance processes.

4.1.1 Smart devices for data acquisition

Miniaturization of technologies is bringing an increased set of devices that capture information in varied ways: Two examples are included below:

Concerning lubricant sensors, at the top of the technological development (diffraction gratings, miniaturised systems, micro optical systems, etc.), optical micro-sensors are being developed for measuring visible and infrared wavelengths that can be correlated to many different fluid properties, providing reliable readings for many parameters that was only possible to analyse with laboratory equipment. With appropriate communications with central intelligence systems, smart sensors can be able to run unattended, performing self-tuning and auto-calibration, etc. The most important advantage is, of course, the achievement of much reduced sensor sizes, which could even rival those of vibration sensors. This can allow the introduction of laboratory-like detection systems in reduced machinery (engines, hydraulics, compressors…) On the other hand, even though sensor prototyping has a cost, it is also foreseen a low cost of micro-fabrication, when using silicon-based materials replicated on polymers.

Likewise, RFID and smart tags are the basis to the technology which is rapidly emerging as the replacement for the barcode. In fact, RFID systems are beginning to making an impact on manufacturing and logistics operations and it is believed that advantages may also be gained soon in the maintenance field. Smart tags and RFID interoperation with rest of the technologies, together with clear applications of this potential have been recently investigated (reference?). With tags able to store and communicate identity and historical information, it has been possible to understand how users of such technology would enjoy immediate access to information including machinery data, sensor identification, audit trails of maintenance activities, spare part information and use of maintenance tool. Although cost is a major factor limiting the uptake of this technology by companies at the present time, it is recognised that this will become less of a factor as micro-manufacturing costs decreases and operating efficiencies are squeezed to higher and higher requirement levels. The ability of businesses to plan accordingly and, in emergencies, react quickly is one key advantage of these new techniques.

4.1.2 Smart PDAs and ubiquitous computing in process oriented maintenance

Another field were miniaturization of technologies is playing an important role is on the appearance of multiple sources of computing. First, this makes possible to have the computing power at operator’s hand, and second this will be extended with devices that may be mimicked with the area surrounding the operator. Given this, ambient Intelligence emphasises on greater user-friendliness, more efficient services support, user-empowerment, and support for human interactions. In this vision, people will be surrounded by intelligent and intuitive interfaces embedded in everyday objects around us and an environment recognising and responding to the presence of individuals in an invisible way.

Smart PDAs and portable devices are the first examples of a ‘wearable’ computing power. Even though they are already interesting for certain maintenance process, they are still today being turned into more cost-effective tools thanks to the packing of new functions (RFID, GPRS,…) as well as to the reduction in costs. Adding the ease and flexibility of carrying a handheld wireless device, mobile computing has the potential to transform the way a range of industrial management, monitoring and control tasks are performed (Buse and Wu 2004). This potential is still largely unexplored in maintenance management. For instance, integrated maintenance management solutions based on combined usage of wireless sensing, RFID tags, hand-held devices and central or remote server-side computing and data-offices (Legner and Thiesse 2006) are still in their infancy.

As an example of future involvement of these devices, within DYNAMITE, the usage of PDA devices plays a key role in bringing Mobile Maintenance Management closer to the daily practice at the shop floor. PDAs are used in synergy with intelligent sensing devices and smart tags on the lower-end of the data processing architecture, but also with central server's databases and data processing and remote access applications at the higher-end of the architecture. PDA are expected to become a ubiquitous expert advisor and, at the same time, a flexible data collector. Likewise, in TATEM, one of the main issues (process oriented maintenance) has been fully supported in appropriate ubiquitous systems, where smart

PDAs are the main support, that may guide maintenance operator to the execution of any kind of tasks even at adverse operation conditions (e.g. at night) or under time constraints.

4.1.3 Intelligent web services and machine learning systems for diagnosis and prognosis

Another series of technological drivers for the application of new technologies have much to do with the actual status of automation systems and ‘computational intelligence’, and the tools readily available to help to model a maintenance tasks.

Most existing commercially available products only perform inferential steps. This is because learning -any change in diagnostic knowledge- is very difficult to be encoded once a business process is placed on a system. However, changes concerning most of the monitored machinery may appear everywhere, so ability to modify the inferential steps is a must (Arnaiz & Gilabert 2004). In fact, learning abilities is really what makes us consider a system as ‘intelligent’. It is not possible to consider a system as ‘intelligent’ when it keeps on making the same mistake forever. Given this, learning can come in two different ways: As a batch fully data-dependant process, where a model is constructed out of a data system, and as a incremental approach, where existing model is slightly modified by new data (or expertise).. These adaptive systems are the main focus of research concerning ‘incremental’ updating of the knowledge systems, and there exist sound paradigms to incorporate this abilities in both diagnostics and prognostics systems (CBR, Bayesian Networks, Reinforcement Learning, Neuro-Fuzzy systems)

Web services represent an important development of the use of the Web. Initially the Web was used to transport pages of HTML from a files system somewhere on the internet to a browser which would render it and display it to a user. On the other hand, there exists interoperability protocols such as DCOM/COM+ or CORBA. What is actually novel is the use of a plain text format for the exchange of messages as well as a standard Internet protocol such as HTTP / TCP for message transport. This guarantees that any machine connected to the net will be able to participate in an interoperability (Web Service) Exchange since HTTP is usually always open on even the strictest firewall configurations.

Given this, it has been tagged as very interesting to try not to substitute any existing legacy system, but to provide added ‘intelligence’ to existing systems (such as .an ERP or CMMS systems) much in the same way a new sensor adds new data to the ‘pool’ of information managed by maintenance operators. This has been tagged as a ‘plug & play’ concept. CMMS should, for instance, request business to process such new data in a way not previously thought (e.g. advanced diagnostics)   In particular, DYNAMITE has created a framework for the inclusion of these services as web business processes capable of performing intelligent actions on demand, from a pool of competing resources (i.e. a web service fro diagnosis based on FTA information vs. a service based on expertise for engine diagnosis based on compound lubricant and vibration information)

4.2 What standards for interoperability can provide? – OSA-CBM

The interoperability between technologies usually requires a lot of effort, but there are today several standards that may help in the process of the development of appropriate architecture and communications. Letting aside the variety of standards for wired and wireless communication protocols, it is important to focus on the ‘logical’ architecture of the solutions.

In particular, a complete CBM system may be composed of a number of functional blocks or capabilities: sensing and data acquisition, data manipulation, condition monitoring, health assessment/diagnostics, prognostics, and decision reasoning. In addition, some form of a

Human System Interface (HSI) is required to provide a means of displaying vital information and provide user access to the system. Thus, there is a broad range of system level requirements that include: communication and integration with legacy systems, protection of proprietary data and algorithms, need for upgradeability, and reduction of engineering design time and costs.

With these requirements in mind, OSA-CBM[10] (Open System Architecture for Condition Based Maintenance) is designed as an open non-proprietary CBM communications framework to provide a functional platform flexible enough to suit a broad range of applications. The goal of OSA-CBM, well described by Bengtsson (2004), is the development of a layered architecture (and data exchange conventions) that enables interoperability of CBM components, intended to cross the gap between computer scientists and program managers and systems integrators.

It is important to point out that both DYNAMITE and TATEM have made OSA-CBM the core architecture to build the solutions. The 7 layers of the architecture have offered a very good way to distribute the business process needed, and to decide up to what level a process should be on-board an aircraft or off-board, or can be accessed by intelligent sensor systems or not, etc.

OSA-CBM standard is maintained by An Operations and Maintenance Information Open Systems Alliance (MIMOSA). This is a second standard that, based also in another architectural specification (OSA-EAI Open System Architecture for Enterprise Application Integration) offers an exhaustive set of data base specifications to develop maintenance related solutions. This is a growing standard, being adopted by many companies offering connectivity to big solution providers in ERP or CMMS systems, that has also been a central point of the DYNAMITE components development..

[10] http://www.mimosa.org

5 E-maintenance organization examples

5.1 Dynamite – Dynamic decisions in maintenance

The DYNAMITE vision aims at promoting a major change in the focus of condition based maintenance, essentially taking full advantage of recent advanced of information technologies related to hardware, software and semantic information modelling. Special attention is also given to the identification of cost-effectiveness related to the upgraded CBM strategies, as well as to the inclusion of innovative technologies within CBM processes. It is expected that the combination of the use of new technologies together with a clear indication of cost-benefit trade-off will facilitate the upgrade into CBM.

This expectation is thought to be particularly relevant in many cases where non-critical machinery exists, and especially for the vast majority of SME companies where the distance between planned and condition based maintenance is too wide. However, it is difficult to find a single solution that fits for all concerning the maintenance needs, as was shown in Arnaiz *et al.* (2007).

Therefore, a new concept (DYNAWeb) has been developed. This concept is best described as the information and communication platform that provides operational interaction between ‘plug-in’ technologies in the framework of a distributed information scenario, where technologies of interest may vary from a maintenance use case to another (Jantunen *et al*. 2008).

Figure 11.3 provides a schematic overview of the complete system concept depicted for information and communication technologies that are considered within DYNAMITE project. This view identifies the existence of three layers (squared blue on the right of the figure 11.3) with the location of different actors with respect to the operation processes within the company. The figure 11.3 also states the interoperability of these actors with different technologies.

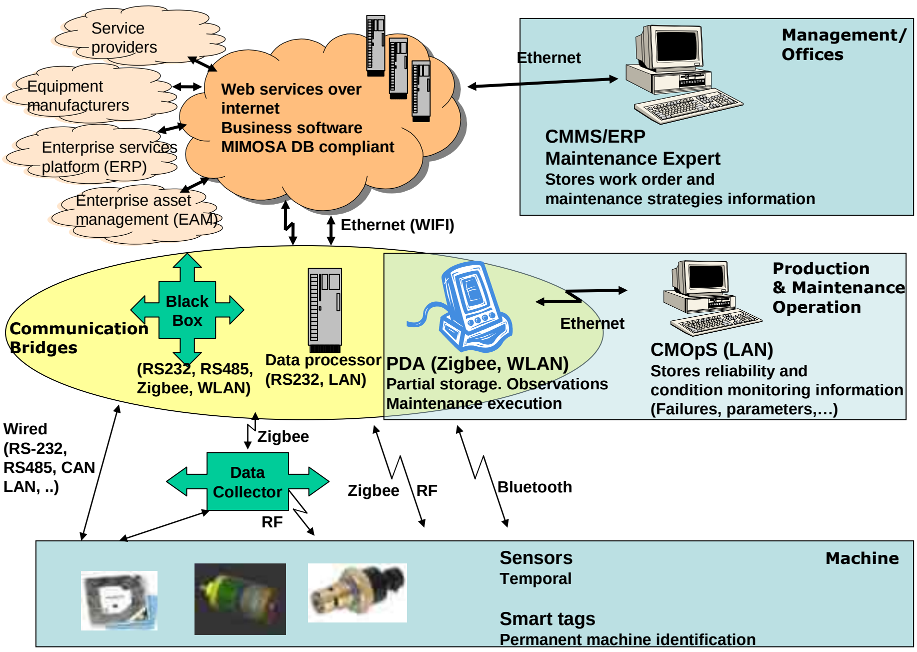

Figure 11.3. DYNAWeb ICT structure

The platform is flexible enough to provide intelligent processing 'on-demand' and ubiquitously, with a three-level configuration of web services, agents and interfaces that facilitates interoperability with existing legacy systems. Finally, the platform can grow according to the needs of the user (e.g. new information, increased knowledge on the process, new measurements, etc). The DynaWeb solution finally tested already integrates 28 hardware and software components, including smart MEMS sensors with energy harvesting, on-line lubrication sensors, smart tags for identification and location of components, maintenance actions supporting handheld mobile computers (PDA), wireless communication and a strategic and economical decision support system.

5.2 Tatem- Technologies and tools for advanced maintenance in aerospace

Maintenance activities can account for up to 20% of an airline's direct operating costs. Despite trends towards outsourcing the proportion of operating costs associated with maintenance has remained at around this level for the last 30 years. There is, however, scope for bringing improvements to the maintenance process. For example, it is estimated that line mechanics spend 30% of their time trying to access information to diagnose and rectify failures; in a recent survey the incidence of human error in the maintenance task has been estimated as contributing to 15% of aircraft accidents.

Looking to the future aircraft fleet sizes there is concern that there will not be enough trained maintenance engineers. In addition demands on the maintenance personnel are increasing due to the increased variety in the types of aircraft used by an airline, the demand for increased aircraft utilisation and the required close monitoring for ETOPS flights.

The objective of the TATEM Integrated Project has been to validate technologies and techniques which can be used to transfer unscheduled maintenance to scheduled maintenance and provide the means to make the maintenance task more efficient and effective. The technologies and techniques to be validated included:

- Novel onboard sensor technology to gather data from the aircraft systems (avionics, utilities, actuation, engines and structures)
- Signal processing techniques (e.g. fuzzy, logic, neural networks, model-based reasoning) which can be used to convert data into information about the health of the systems.
- Diagnostic methods to identify and locate failures and malfunctions and so reduce the number of incidences of no fault found
- Prognostic methods to provide support for preventative maintenance actions
- Decision support techniques to generate process-oriented information and guidance
- Human interface technologies to provide the ground crew with information, data and advice at the point of work.

This will have a direct impact on the operation and maintenance efficiency and costs, reducing not only the need for scheduled and unscheduled maintenance, but also human errors and training costs concerning maintenance activities.

The project, leaded by Smiths Aerospace, Airbus and EADS, has different strands of research, tough there is a special strand aimed at providing Ground Crew support activities. This is a key part of the project in order to implement effective procedures for efficient O&M, based on the intelligent information coming from newly added on-board sensors and intelligent software system. Two of these procedures are:

- **Operational reliability:** Reduce the number **o**f unscheduled maintenance events while the A/C is in operating by deferring part of the maintenance actions until night stops, hangar checks, arrival to airports with best maintenance facilities, etc
- **Balanced maintenance:** Optimize the resources (human and material) avoiding uneven workload distributions, high spares needs, etc.

6 Conclusions

From the industrial and scientific material already available, E-maintenance is justified not only in relation to the new technologies used but also to new expected services leading to make a first step in maintenance revolution mainly based on mobility capacities. Some E-maintenance platforms are shown to highlight concrete applications of e-maintenance in industry. A next step now is to structure from a academic point of view, the e-maintenance community in order to propose it as a new science.

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8.6 Mapping FMEA into Bayesian Networks

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Resumen

Este artículo detalla una metodología para crear un sistema de diagnóstico de fallos mediante Redes Bayesianas, a partir de la información de Análisis de Modos de Fallos y Efectos (AMFE) Aplica la metodología a un motor diésel marino, y muestra su uso en una aplicación de diagnóstico que utiliza un conjunto de sensores de aceite lubricante en línea. La asignación de todo el conocimiento que contiene un AMFE a una Red Bayesiana permite desarrollar aplicaciones de software para el mantenimiento, usando su estructuración de componentes y subcomponentes y a su vez las cadenas de causa-fallo-efecto.

Mapping FMEA into Bayesian Networks

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ABSTRACT

FMEA is a useful tool that helps to find possible flaws in a system or element, mainly in the design phase. But it is a mere document that has no further "direct" use than the observation. Mapping all this knowledge into a Bayesian Network would make it possible to use the information in further ways, like software applications for maintenance. A good FMEA has the necessary features to build a good Bayesian Network: Bottom-up (or Top-Down) analysis of all the components and subcomponents and cause-failure-effect chains.

In this document we will detail the steps followed to create the Bayesian Network, using the FMEA of a Marine Diesel Engine, as well as the use of it in a diagnosis application that uses a set of on-line lube-oil sensors.

Keywords

FMEA, Bayesian-Networks, Diagnosis

1. INTRODUCTION

A well designed FMEA is a useful and valuable information source, containing both component and system failures, causes and effects. This information, however, is a mere document which cannot be used in further “direct” ways. If correctly mapped into a Bayesian Network it could be used in other ways, such as software applications. While the FMEA is mainly used to locate design flaws *before* the system is completely deployed, the Bayesian Networks objective is to help locate problems before they occur in a working/deployed system. Furthermore, a Bayesian Network can be helpful when it comes to visualize all the cause-effect chains involved in the system contained in the FMEA.

This article will show the used methodology to map a FMEA into a Bayesian Network, which will be later used to give a diagnosis of the status of the engine, using a series of on-line oil/lube sensors.

2. FMEA

FMEA (**F**ailure **M**odes and **E**ffects **A**nalysis) is a procedure in operations management for analysis of potential failure modes within a system for classification by severity or determination of the effect of failures on the system. It is widely used in manufacturing industries in various phases of the product life cycle and is now increasingly finding use in the service industry.

Failure modes are any errors or defects in a process, design, or item. These failures appear due to one or more causes, which can be effects of other failures. The failures modes are rated by 3 parameters: Severity, Occurrence and Detection, with values ranking from 1 to 10.

- Severity: The impact that this failure has in the system or client	1 Little effect … 10 Catastrophic
- Occurrence: The probability of this failure happening.	1 Very improbable … 10 Sure to happen
- Detection: The ability to detect this failure	1 Easily detectable … 10 Undetectable

The product of these parameters is the RPN (Risk Priority Number). The RPN merely ranks the failure in the system, giving the reader an idea of the “risk” of the failure happening.

$$RPN = S * O * D$$

3. BAYESIAN NETWORKS

A Bayesian Network (BN) is a probabilistic graphical model [1][2].It reflects the states of some parts of a world that is being modelled and it describes how those states are related though conditional probabilities. All the possible states of the model represent all the possible worlds that can exist, that is, all the possible ways that the parts or states can be configured.

The representation is a directed acyclic graph consisting of nodes, which correspond to random variables and arcs, which in turn correspond to probabilistic dependencies between the variables. A conditional probability distribution is associated with each node and describes the dependency between the node and its parents. BNs are widely used in diagnosis. E.g.: Given symptoms, the network can be used to compute the probabilities of the presence of various diseases.

In the network prototype shown in Figure 1, the qualitative relationship indicated by the direction of the link arrows corresponds to dependence and independence between events. That is, nodes higher up in the diagram tend to influence those below rather than, or, at least, more so than the other way around. On the other hand, the quantitative relationships between nodes are defined by conditional probability tables (In case of continuous variables, conditional probability distributions)

Many practical tasks can be reduced to the problem of classification, including Fault diagnosis. A Bayesian Network helps tackle the problem of classification in a way that helps to overcome problems that other methods partially address:

- Able to mix a-priory knowledge together with data/experimental knowledge.
- Explanatory abilities
- Uncertainty and Causality management
- Learning both parametric and structural issues.

One important characteristic of this inference model is the adaptation ability. In this way, introducing risk values of environmental variables and expected parcel risk value, the Bayesian Network adapts the weights of conditional probability tables, approximating to desired solution.

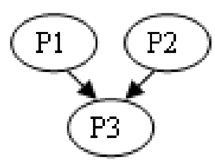

Figure 1: Bayesian Network with 3 nodes

4. BUILDING THE MODEL

Bobbio and Portinale detailed in [3] a methodology for mapping Fault Trees into Bayesian networks. Using FMEAs to do the mapping works in a similar way, using cause-effect chains to propagate belief.

The methodology used to do the mapping will be bottom-up, starting from the individual components and subsystems, to finish with the whole system. Three types of nodes will be used: Failure, Component Failure and Effects. Failure nodes represent a general failure in the system. Component Failures represent specific failures happening to a component. Effects are the result of a failure (general or component) which don't further cause more failures in lower levels. They act as "leaf" nodes. A fourth node type can be used (Component) to help locate in which component is happening the failure.

4.1 Mapping Methodology

The steps to build the networks should be:

1. *Start with the component failures*. Add the component failures to the network as nodes.
2. *Add the component failure modes*. The component failure modes should have arrows pointing from each component failure node. This identifies the component failure modes as being specific realizations of the component failure and corresponds to the FMEA beginning with a component failure and then subdividing it into failure modes. Pointing the component failure modes to the component failure node instead of from it can also be done. If the failure modes point to the failure node then the failure modes are the centers of the network instead of the component failure nodes. Note that the component failure node is really not necessary and simply serves to organize the different failure modes.
3. *Add the failure mode effects.* Add the effects of each failure mode with arrows pointing from the failure mode to the effect.

4. *Add the failure mode causes*. Add the causes for each failure mode with arrows pointing from the cause to the failure mode.
5. *Merge common nodes.*
    a. *Common effect.* Merge the common effects of different failure modes into one common effect.
    b. *Common cause.* Merge the common cause of different failure modes into one common cause.
    c. *Join cause-effect relations.* Join the effect of one failure mode as a cause of another failure mode by pointing an arrow from the effect as a cause of the other failure mode.
    d. *Join components failure.* A failure mode can be the cause of another failure mode

For a better understanding of the process, here is a step-by-step example

The next table shows the FMEA extract that will be used in the example. The table contains the cause-effect chains of three components of a diesel engine: injector, cylinder liner and piston.

Figures 2 to 6 show the node-adding steps. Figure 7 shows the fusion between the different components causes and effects.

Table 1: Example FMEA (extract)

Component Failure	**Failure Mode**	**Cause**	**Effect**
Injector	Bad Spray	Sticky Needle	Bad Lubrication
			Piston Perforation
Cylinder Liner	Bad Lubrication	Bad Spray	Overheating
		Bad Oil Quality	Piston Clipping
Piston	Piston Perforated	Bad Spray	Perforation particles.
	Piston Clipped	Overheating	Clipping particles
		Bad Lubrication	

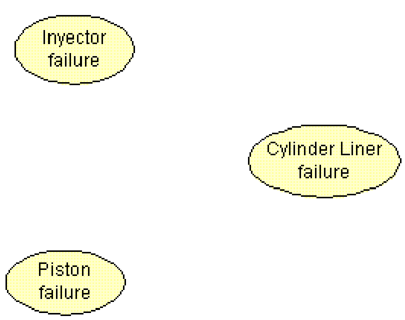

Figure 2: Adding component nodes

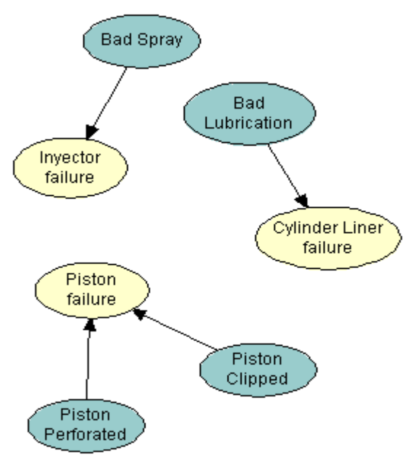

Figure 3: Adding failure nodes

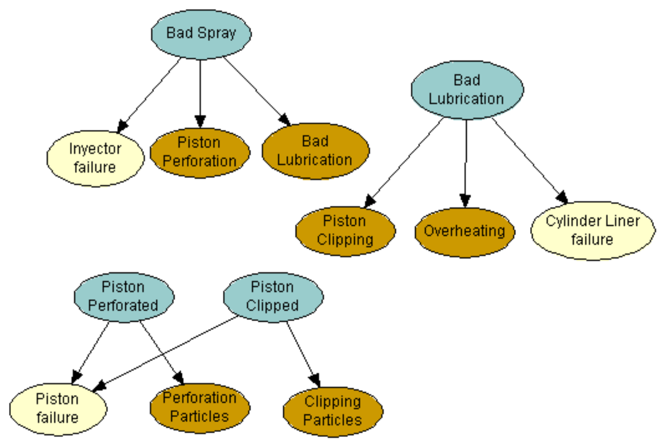

Figure 4: Adding effect Nodes

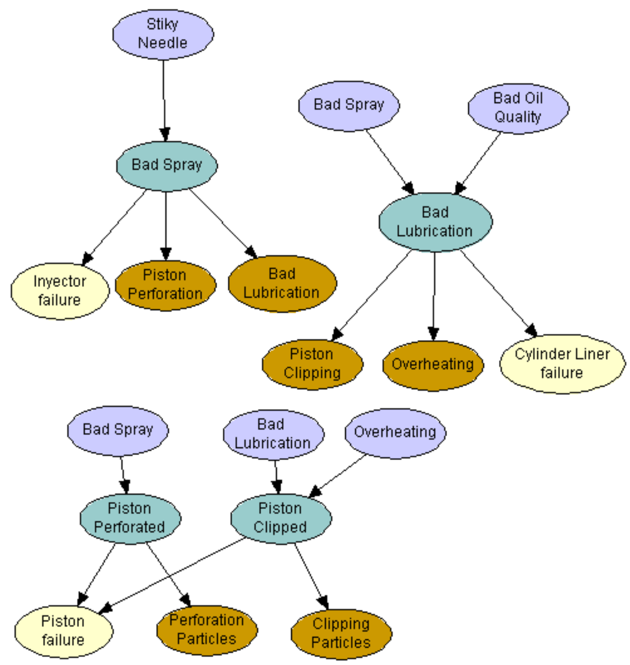

Figure 5: Adding cause nodes

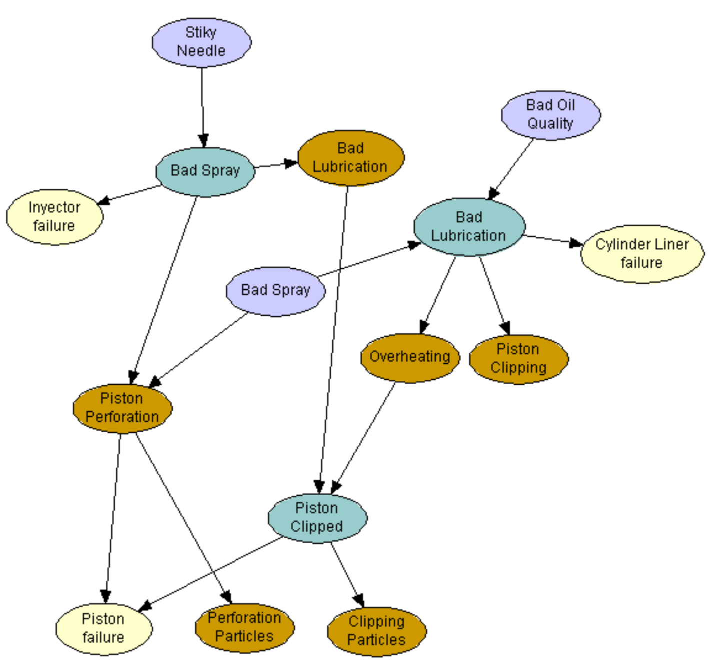

Figure 6: Merging common causes and effects

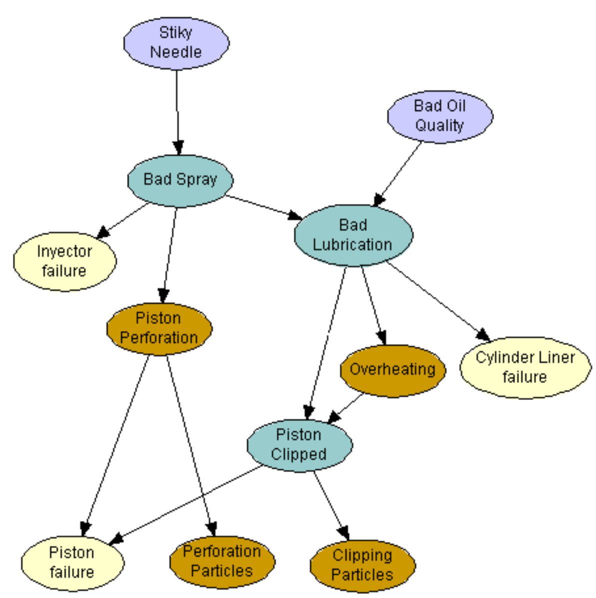

Figure 7: Joining Failure modes and causes

4.2 Assigning probabilities

Assigning probabilities to the network and nodes is the most difficult part of the mapping. The nodes in the Bayesian network will be of Boolean nature. The fail happens or not, the effect is visible or not, the component works or not… These nodes should be assigned probabilities differently depending on how the failure happens.

The FMEA Occurrence rate should be used for assigning the probabilities of the nodes. The rate is ordinal, not linear (An occurrence rate of 8 is more probable than a 4, but doesn't mean that is as twice as probable) and not standardised, so each FMEA may rank the occurrence rates in different ways (occurrence rate of 5 could be a probability from around 0.1 to 0.001, depending on the FMEA). Figure 8 shows some of these probabilities and occurrence rates [4]

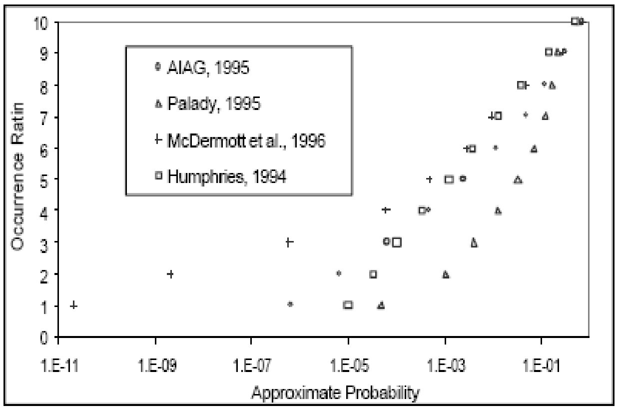

Figure 8: Probabilities and occurrence rates

FMEA do not contain probability information about the cause nodes. Cause nodes are the nodes that don't have any dependencies. In the FMEA in Table 1 the occurrence rate to assign the probability of a bad spray due to a sticky needle could be used, but the probability of the needle being sticky is unknown. These probability values should be set using prior studies, extra data or information or an expert's opinion.

Table 2: Piston probability table (Binary OR)

Piston Perforated	True		False	
Piston Clipped	True	False	True	False
Faulty	1	1	1	0
Normal	0	0	0	1

Nodes that are dependant from more than one parent nodes act differently depending of their nature. Most of the failures happen when one or more of their causes are present. Noisy OR-gates [16] are used for this, which are a generalization of the binary OR-gates. If a failure has *n* possible causes, for each one of the x_i causes there is a probability p_i, which is the probability of the failure being present when the cause x_i is present and all the others are absent.

$$p_i = P\left(Failure \middle| \; x_i \; only\right) = P\left(Failure \middle| \; \overline{x_1}, \overline{x_2}, \cdots x_i \cdots \overline{x_n}\right)$$

The probability of any combination of active causes is then calculated by the next equation:

$$P\left(Failure \middle| x_1, x_2 \ldots x_n\right) = 1 - (1 - p_1) * (1 - p_2) * \ldots * (1 - p_n)$$

$$P\left(Failure \middle| X\right) = 1 - \prod (1 - p_i) \text{ Where X = all active } x_i \text{ causes}$$

Table 2 and Table 3 show the difference between using binary Or-gates and Noisy OR-gates, detailing the probability tables for the Piston node in Figure **6**

Table 3: Piston probability table (Noisy OR)

Piston Perforated	True		False	
Piston Clipped	True	False	True	False
Faulty	0.98	0.9	0.8	0
Normal	0.02	0.1	0.2	1

Some failures may need more than one cause simultaneously in order to happen. Noisy AND-gates can be defined using the same considerations used with the Or-Gates [3]. In this case each of the individual probabilities p_i is defined by the probability of the failure being present when all the causes **except** for x_i are present.

$$p_i = P\left(Failure \middle| \; all \; but \; x_i\right) = P\left(Failure \middle| \; x_1, x_2 \cdots \overline{x_i} \cdots x_n\right)$$

The probability of any combination of active causes is then calculated by the next equation:

$$P\left(Failure \middle| x_1, x_2 \ldots x_n\right) = p_1 * p_2 * \ldots * p_n$$

$$P\left(Failure \middle| X\right) = \prod p_i \text{ Where X = all active } x_i \text{ causes}$$

Table 4 shows the probability if we considered that a piston needs to be both perforated **and** clipped to be faulty.

Table 4: Piston probability table (Noisy AND)

Piston Perforated	True		False	
Piston Clipped	True	False	True	False
Faulty	0.72	0.9	0.8	0
Normal	0.28	0.1	0.2	1

Noisy OR-gates work under the assumption that all the possible causes of the failure happening are previously known. This is not always possible as there could be unknown causes that have not been noticed or recorded in the FMEA. An additional parameter called *leak* is added to fix this [17]. The leak constitutes a kind of residual “all others” category, representing what is not explicit in the FMEA, and makes it possible the failure to happen even if neither of their recorded causes is present.

To use the Noisy OR-gates and AND-gates, the probability of the failure happening for each of the individual causes needs to be known. When the probabilities are unknown, there is no way of knowing which cause has more relevance in the failure happening. One solution to this is to use Maximum entropy theory. Maximum entropy (ME) theory argues that in the absence of other information, all s failure states of a variable X should be assigned equal probabilities of (1/s), as shown in Table 5.

Table 5: Max. Entropy table in a node with 3 causes

Node 1	True				False			
Node 2	True		False		True		False	
Node 3	True	False	True	False	True	False	True	False
True	1	0.66	0.66	0.33	0.66	0.33	0.33	0
False	0	0.33	0.33	0.66	0.33	0.66	0.66	1

All the probability values can be later edited to specific values, which can be obtained from extra design information, experts, reliability tests and field performance evaluations [5].

Sometimes, different variables can be considered as different grades of a common variable. E.g. the nodes "No Power outcome" and "Power outcome not enough" can be considered different states of the power outcome of the engine. Instead of using two Boolean nodes it is possible to use a variable named "Power Outcome" with the states Normal, Poor and None. Using this kind of multistate variables can lead to smaller networks, at the expense of more complex probability tables.

There are also many good references on techniques and guidelines for estimating probabilities which can be very useful for developing your own model [6][7][8][9][10][11].

5. DIAGNOSIS APPLICATIONS

Once created the Bayesian Network, it can be used in more than one way. In this paper, two different diagnosis applications will be used. One is an independent application specific made to help locate failures in large diesel engines used in marine cargo vessels. The other one is the integrated on-line web platform TESSnet, which gives diagnosis and prediction support to a variety of sensors.

A series of parameters of the lubricant oil will be analysed in order to run a diagnosis over the status of the engine, parameters such as viscosity, particles and insoluble content, soot...

Some failures will cause these parameters to appear. Incomplete combustion will increase the soot, piston clipping and perforation will increase the number of clipping and perforation particles in the oil, and so on.

All these oil parameter values will be stored in a database, where they will be used later by both applications. In order to accomplish this, a GPS modem connected to the sensor will send the measurements timely, while another GPS modem will receive and store the transmitted values into the database.

Both applications will follow the same steps in order to realize the diagnosis [Figure 9]:

1. Retrieve sensor data from the database. The application will connect and retrieve the last measurements made by the sensor.
2. Discretize numeric values. The Bayesian Network uses Boolean values, so first of all it is necessary to turn the numerical values into Boolean ones. Maximum and Minimum values can be used for this. E.g. If the Soot concentration is above 50%, the Soot node status is set to True.
3. Propagate belief. The Boolean values are assigned to the parameter nodes, then the belief is propagated though the network.
4. Retrieve data from the failure nodes. Once the propagation is completed, the updated belief values of the failure nodes are retrieved.

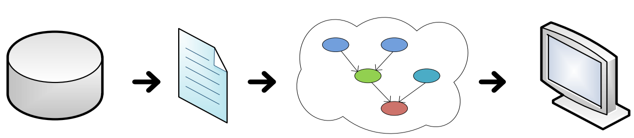

Figure 9: Information flow in application

In this way the data capture and the diagnosis work asynchronous and independently. Other type of sensors can be used to gain additional information (vibrations, temperature...)

The Bayesian Network has been created with the HUGIN Expert tools [12][Figure 10]. HUGIN Expert provides Bayesian Network creation and design software as well as plug-ins to integrate its features with different platforms and programming languages. Other alternative software to implement the Bayesian Network is GeNle 2.0. As opposed to HUGIN, GeNle is freely available on the internet without charge and is an excellent tool, easy to use and quite capable [13]. Also BN software Samlam can be very useful to built reliability applications [14].

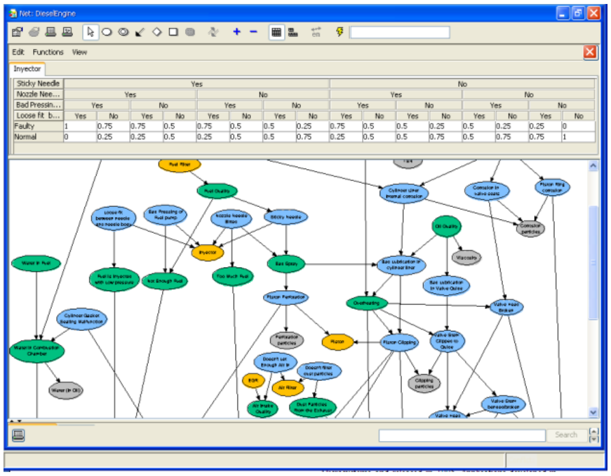

Figure 10: HUGIN Researcher

5.1 Diesel engine application

The independent application was specifically created and designed for diagnosing the status of a marine diesel engine [Figure 11]. When the button is pressed, the last measurement is retrieved from a database, along with his parameter values. These parameters are then discretized into Boolean values and assigned to the net. Once the belief is propagated through the network, the failure modes and component status are showed, both numerically and in a colour rate (Normal, Warning, and Danger).

The actual version of the application includes a test interface, which lets the user try all the possible input combinations of the network and its influence in all the nodes of the network. Future versions of the application may include a prognostic service, using trends developed from a set of previous measurements; and the possibility of configuring both sensor inputs and displayed nodes.

The application has been developed in Java [15], making it possible to run in any platform.

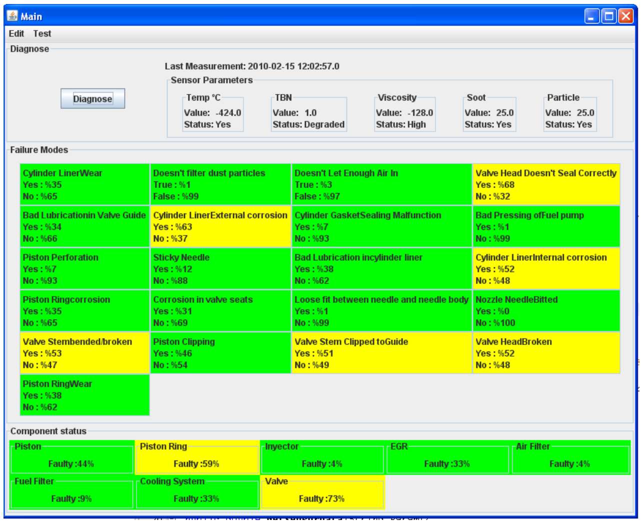

Figure 11: Diesel Engine Application

5.2 TESSnet

The web platform was developed by Fundación Tekniker. TESSnet is a web platform which can be used as Predictive Maintenance Management System (PMMS) [Figure 12]. Company and plant information can be accessed from the website, along with machine and assembly status, and sensor and measurement information is stored as well.

Specific parameter values can be viewed, along with trend charts. Using these trends and setting maximum and minimum values to the parameters, the platform gives prognostic of the assemblies in terms of the remaining useful life. Diagnostic is provided with a rule based system. E.g. If the parameter *X* surpasses the warning value, the possible cause is *Y*.

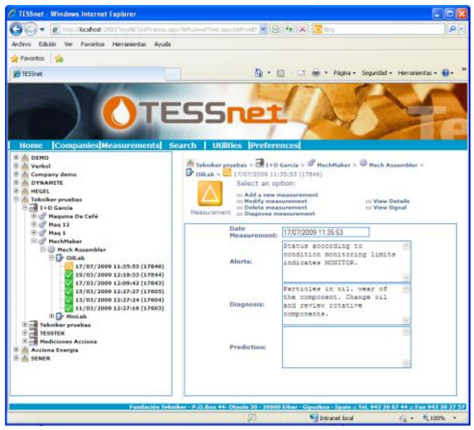

Figure 12: TESSnet

The Bayesian Network would replace the rule based system. The data retrieval, discretization and propagation steps would be the same as in the other application. The results, numerical and discretized, would then be shown in a textbox.

The main drawback is that each system would require his specific Bayesian Network, as TESSnet contains information about different systems like aero-generators or machine tools. However, for similar systems it could be possible to easily create a new Bayesian Network, changing some parameters or probabilities, adjusting them to the new system.

6. CONCLUSIONS

The method explained in this paper tries to provide some help in the task of building Bayesian Network out of a FMEA. The FMEA usually have good information about cause-effect chains, but lack of proper probabilistic information, so the resultant network will be of fixed structure and adaptive probabilities.

This paper has also described some mechanism to solve the lack of probability information, developing a Bayesian Network for marine diesel engines, which has been used in two applications

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8.7 An e-maintenance architecture for diagnosis automation

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Resumen

El contenido de este capítulo presenta una plataforma de servicios web lista para integrar capacidades de procesamiento inteligente de acuerdo con la arquitectura OSA-CBM. Esta plataforma es parte de una infraestructura de comunicación flexible, apodada DYNAWeb. El capítulo también presenta servicios web inteligentes que llevan a cabo tareas de diagnóstico utilizando modelos probabilísticos basados en datos de condición. Finalmente, se presenta TESSnet, un sistema que se puede identificar como un sistema de administración de mantenimiento predictivo (PMMS), que aprovecha las ventajas de los servicios web para mejorar sus tareas operativas. Uno de los servicios clave en esta infraestructura está dedicado a propósitos de diagnóstico. En este caso, se ha desarrollado un servicio de diagnóstico utilizando una Red Bayesiana, teniendo en cuenta la información compilada a partir del modo de fallo y análisis de efectos de una unidad de cogeneración.

An E-maintenance architecture for diagnosis automation

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Fundación Tekniker, Spain

1 Introduction

One of the main aims of the recently finished EU-funded Integrated Project DYNAMITE (Dynamic Decisions in Maintenance) has been to bring together a group of technologies that can be integrated in a structured way, yet flexible enough to allow the selection of a particular subset of the technologies. The main idea behind the platform is a series of “plug and play” hardware and software components that can be included on demand in any existing use case, without a need to remove any legacy system.

One of the key services in this infrastructure is devoted to diagnosis purposes. In this case, has been developed a diagnosis service using a Bayesian Network, taking into account the information compiled from the Failure Mode and Effects Analysis of a co-generation unit.

The content of this chapter presents a Web Services platform ready to integrate intelligent processing capabilities according to OSA-CBM architecture. This platform is part of a flexible communication infrastructure, nicknamed DYNAWeb. The chapter also presents a intelligent web services that carries diagnosis tasks using probabilistic models based on condition data. Finally, TESSnet will be introduced, a system that can be identified as a predictive maintenance management system (PMMS), which takes advantages of the web services to improve their operational tasks.

2 Web services system in e-maintenance

Web services are a well known technology which has been utilised in industrial environments. They offer interoperability between independent software applications over Internet by means of SOAP protocol which enables the communication [1].

The advantages of web services are the central issue in DynaWeb. Different software modules are able to communicate among them in order to perform a specific task. In this context, to provide the most convenient analysis flow, information processing is understood as a distributed and collaborative system, where there are different levels of entities that can undertake intelligence tasks. Given this, a system architecture has been defined to identify the interactions between actors and the required functions, including 4 layers that correspond to the central information processing layers of OSA-CBM standard [1][2][3]:

1. *Condition monitoring*: It is related to state detection. This layer receives measurements from sensors and their signal processing software. These measurements have to be compared to expected values, and alert should be generated in case of anomaly detection, due to values outside from preset limits or changes in the usual trend.
2. *Health assessment*: The main function of this layer is to set the current health of the asset, in case of an anomaly detected by condition monitoring modules.

It generates health records proposing possible faults, based on health history, operational status and maintenance tasks history. One of the existing diagnosis processes is based on previously developed systems **¡Error! No se encuentra el origen de la referencia.** using Bayesian Networks to facilitate a model that can work with uncertainty and can also be adapted with feedback information.

3. *Prognostics*: This module takes into account data from all the prior layers. The primary focus of the prognostic module is to calculate the future health of an asset, with account taken to the future usage profiles. The module reports the failure health status of a specified time or the Remaining Useful Life (RUL).
4. *Decision support*: Is in this context related to scheduling. CMMS (Computerized Maintenance Management System) schedules work orders based on component predictions. After that it distributes work orders to different operators (PDAs). The PDAs need to read the smart tags in order to learn about the components [4].

One current great challenge is to approach this concept for everyday computing resources (e.g. SMEs), as well as for the mobile services. In fact, regarding the usage of these web services, there are different elements defined which take part in the communication (see Figure 1: Communication architecture among HMI and web services, through the usage of an agent storing data in MIMOSA database)[8]:

1. Human Machine Interfaces (HMI) actor, that is, a software interface for the operator sitting at the desk or walking with the PDA and interacting with local or central database systems asking web services to process specific information.
2. Agent for communicating with DynaWeb web services. The agent is able to collect the needed data from local sources, translating it into the ontology language. In this way the agent acts as an interface between HMI and web service.
3. Web service, performing the requested service, supported by MIMOSA OSA-EAI database.

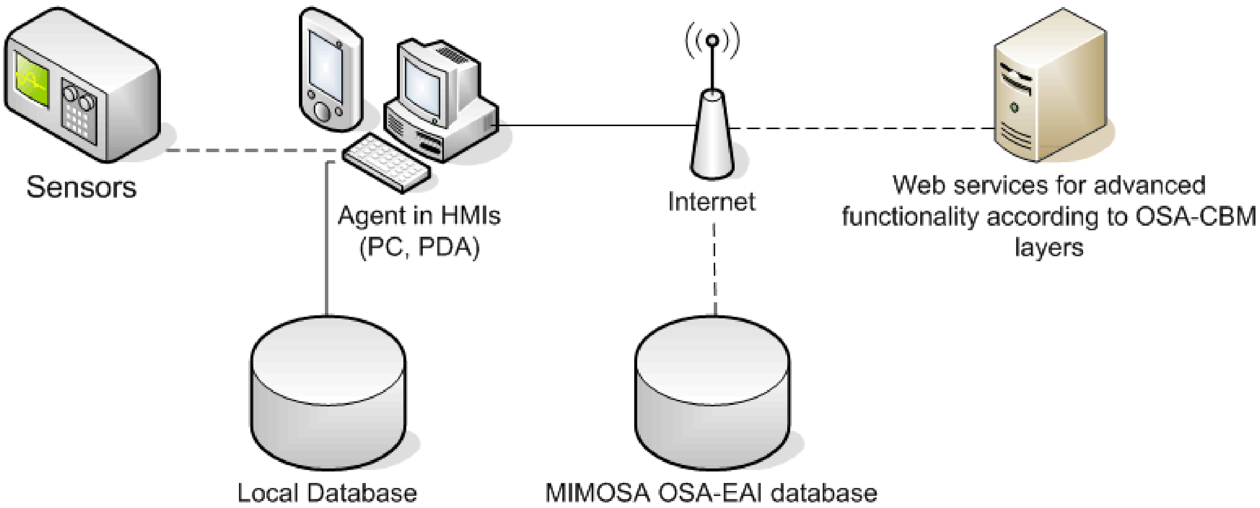

Figure 1: Communication architecture among HMI and web services, through the usage of an agent storing data in MIMOSA database

Another challenge was to adapt this new issue to a traditional approach, where parts of the maintenance tasks are performed from a local support work station. In order to show this feasibility, TESSNet [7] is an example tool used in this framework to perform different tasks by means of DynaWeb web services. It is a predictive maintenance management system based on oil, vibration and temperature analysis which performs an automated condition monitoring, diagnosis, prognosis and decision support. This tool is web-based, collaborative and also offers a distributed management system, with user control access and different access rights. The platform stores measurements both from on-line and off-line sensors as well as laboratory analysis results. The system is connected to the intelligent web services in order to perform the advanced functionality according to OSA-CBM layers. In this way, the feasibility of this approach is demonstrated, where the functionality is not embedded in the platform, but is distributed within a framework. Furthermore, the system avoids the systematic application of corrective and preventive maintenance tasks, making this in a predictive way, with the main objective of performing a balanced maintenance with operational reliability.

3 Diagnosis automation from FMEA

A well designed FMEA (Failure Modes and Effects Analysis) is a useful and valuable information source, containing both component and system failures, causes and effects. This information, however, is a document which cannot be used in further “direct” ways. If correctly mapped into a Bayesian Network it could be valuable information for a software application. While the FMEA is mainly used to locate design flaws before the system is completely deployed, the Bayesian Networks objective is to help locate problems before they occur in a working/deployed system. Furthermore, a Bayesian Network can be helpful when it comes to visualize all the cause-effect chains involved in the system contained in the FMEA.

FMEA is a procedure in operations management for analysis of potential failure modes within a system for classification by severity or determination of the effect of failures on the system. It is widely used in manufacturing industries in various phases of the product life cycle and is now increasingly finding use in the service industry. Failure modes can be any error or defect in a process, design, or item. These failures appear due to one or more causes, which can be effects of other failures. The failures modes are rated by 3 parameters: Severity, Occurrence and Detection, with values ranking from 1 to 10.

- Severity: The impact that this failure has in the system or client
  1 Little effect … 10 Catastrophic
- Occurrence: The probability of this failure happening.
  1 Very improbable … 10 Sure to happen
- Detection: The ability to detect this failure
  1 Easily detectable … 10 Undetectable

The product of these parameters is the RPN (Risk Priority Number). The RPN merely ranks the failure in the system, giving the reader an idea of the “risk” of the failure happening. RPN = S * O * D

On the other hand, a Bayesian network (BN) is a probabilistic graphical model [5][6]. It reflects the states of some parts of a world that is being modelled and it describes how those states are related though conditional probabilities. All the possible states of the model represent all the possible worlds that can exist, that is, all the possible ways that the parts or states can be configured.

The representation is a directed acyclic graph consisting of nodes, which correspond to random variables and arcs, which in turn correspond to probabilistic dependencies between the variables. A conditional probability distribution is associated with each node and describes the dependency between the node and its parents. BNs are widely used in diagnosis. E.g.: Given symptoms, the network can be used to compute the probabilities of the presence of various diseases

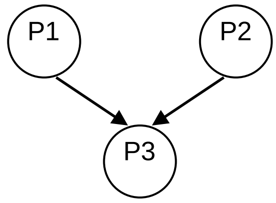

Figure 2: Bayesian network with 3 nodes

In the network prototype shown in Figure 2, the qualitative relationship indicated by the direction of the link arrows corresponds to dependence and independence between events. That is the, nodes higher up in the diagram tend to influence those below rather than, or, at least, more so than the other way around. On the other hand, the quantitative relationships between nodes are defined by conditional probability tables (In case of continuous variables, conditional probability distributions)

Many practical tasks can be reduced to the problem of classification, including Fault diagnosis. A Bayesian network helps tackle the problem of classification in a way that helps to overcome problems that other methods partially address:

- Able to mix a-priory knowledge together with data/experimental knowledge.
- Explanatory abilities.
- Uncertainty management – Causality management.
- Learning both parametric and structural issues.

One important characteristic of this inference model is the adaptation ability. In this way, introducing risk values of environmental variables and expected parcel risk value, the Bayesian Network adapts the weights of conditional probability tables, approximating to desired solution.

The methodology used to do the mapping from FMEA will be bottom-up, starting from the individual components and subsystems, to finish with the whole system. Three types of nodes will be used: Failure, Component Failure and Effects. Failure nodes represent a general failure in the system. Component Failures represent specific failures happening to a component. Effects are the result of a failure (general or component) which do not further cause more failures in lower levels. They act as "leaf" nodes. A fourth node type can be used (Component) to help locate in which component is happening the failure.

3.1 Structure building

The steps to build the networks should be these:

1. *Start with the components:* Add the individual component nodes to the network.
2. *Add the components failure modes:* Add each component's failures
3. *Add the failures effects:* Add each component-failure's effects
    a. *Join common effects:* Two or more different failures may cause a common effect.
4. *Add the causes:* Add the causes of the failures.
    a. *Join common causes:* A cause may have effect in more than one failure.
5. *Establish Cause-effect relationships:* A component failure may be the cause of another component failure.

The Figures from Figure 3 to Figure 7 show the network building steps for the FMEA extract in Table 1

Table 1: small FMEA extract containing 3 components.

Component	Failure	Cause	Effect
Injector	*Bad Spray*	*Sticky Needle*	*Bad Lubrication*
			Piston Perforation
Cylinder Liner	*Bad Lubrication*	*Bad Spray*	*Overheating*
		Bad Oil Quality	*Piston Clipping*
Piston	*Piston Perforated*	*Bad Spray*	*Perforation particles*
	Piston Clipped	*Overheating*	*Clipping particles*
		Bad Lubrication	

Ideally, the used nodes will be of Boolean nature. (The fail happens or not, the effect is visible or not, the component works or not…). Some failures, however, could be considered states of similar nature. E.g. “Battery has low energy” and “Battery has no energy” are 2 independent failure nodes. They could be grouped in a single node called “Battery energy” with 3 states (Normal, Low and No). This will lead to smaller networks, but the probabilities table will be harder to build assign in the next step.

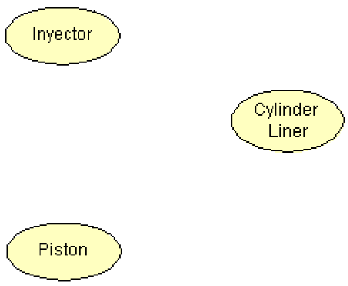

Figure 3: Adding components

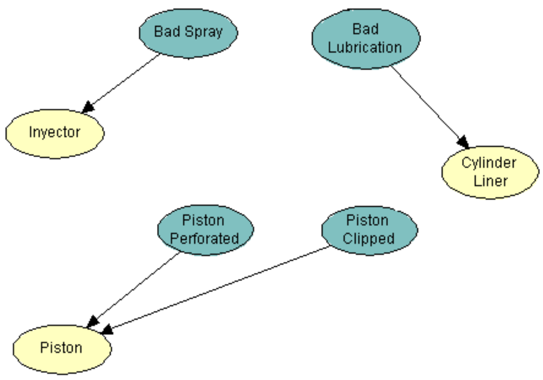

Figure 4: Adding failures

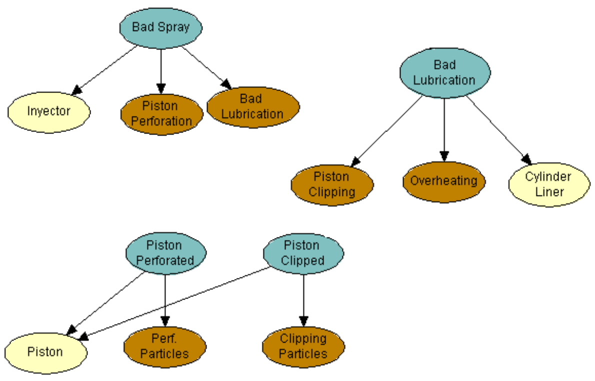

Figure 5: Adding effects

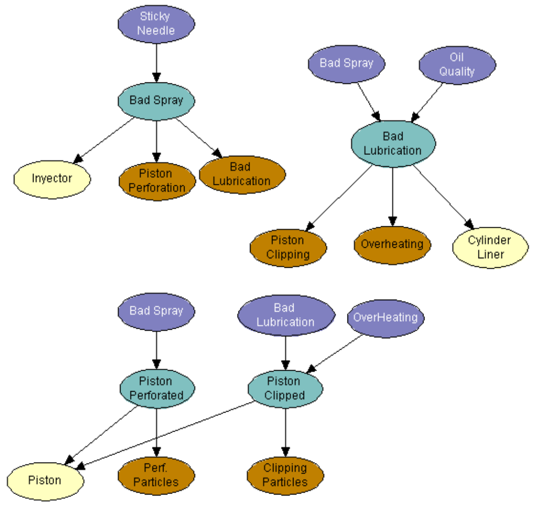

Figure 6: Adding causes

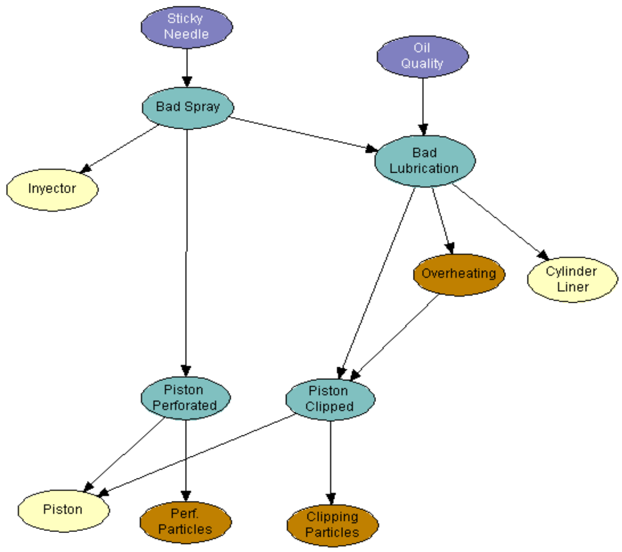

Figure 7: Joining common nodes

Assigning probabilities to the network and nodes is the most difficult part of the mapping. The FMEA Occurrence rate should be used to this, but it is not that simple. The FMEA Occurrence rate is ordinal, not linear (An occurrence rate of 8 is more probable than a 4, but doesn't mean that is as twice as probable) and not standardised, so each FMEA may rank the occurrence rates in different ways (occurrence rate of 5 could be a probability from around 0.1 to 0.001, depending on the FMEA). Figure 8 shows four recommended relationships between Occurrence and probabilities [8].

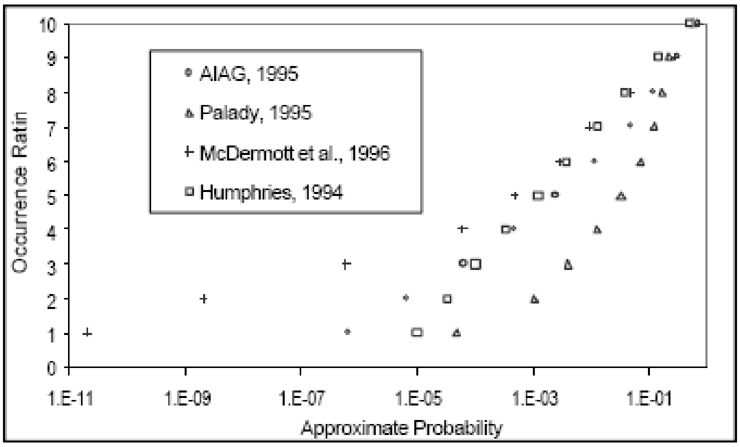

Figure 8: Occurrence rankings and probabilities

The nodes that have dependencies from other nodes should act like logical gates, normally as ‘OR’ gates. The node is activated if any of his parent nodes are activated, as shown in Table 3.

Table 2: Probabilities for nodes acting as OR gates

Node 1	True				False			
Node 2	True		False		True		False	
Node 3	True	False	True	False	True	False	True	False
True	1	1	1	1	1	1	1	0
False	0	0	0	0	0	0	0	1

When a failure has more than one cause it is difficult to know which cause has more relevance in the failure happening. E.g.: An engine piston may get clipped to his liner due to a bad lubrication and/or because the temperature has expanded the piston. Which is the probability of the piston clipping with both causes happening? Which is the probability if only one of them is happening? Which if neither is happening? One solution is to use Maximum entropy theory. Maximum entropy (ME) theory argues that in the absence of other information, all s failure states of a variable X should be assigned equal probabilities of (1/s), as shown in Table 3 [9].

These probabilities can be later edited to specific values, that can be obtained from extra design information, experts, reliability tests or/and field performance evaluations [9].

Table 3: Probabilities according to Maximum Entropy Theory

Node 1	True				False			
Node 2	True		False		True		False	
Node 3	True	False	True	False	True	False	True	False
True	1	0.66	0.66	0.33	0.66	0.33	0.33	0
False	0	0.33	0.33	0.66	0.33	0.66	0.66	1

4 TESSnet, a Predictive Maintenance Management System

The Bayesian Network described has been developed using Hugin Research tool [9]. This software has a graphic interface on windows operating system so that Bayesian networks can be designed and it is possible to see probabilities propagation when node instances are set. An important feature is that Bayesian networks can be embedded into custom applications through an API. Afterwards the Bayesian Networks has been embedded in a web service to be included in DynaWeb. DynaWeb concept is a platform that designs an operational interaction between technologies in the framework of a distributed information scenario, where technologies of interest may vary from a company to another. In this way, every company can select only the modules to use according to their needs, since the approach of this platform is to provide ‘plug&play’ technologies.

TESSnet is the tool used in this framework to perform different tasks by means of Dynaweb’s web services. It is predictive maintenance software based on oil, vibration and temperature analysis which performs an automated condition monitoring, diagnosis, prognosis and decision support. This tool is web-based, collaborative and a central management system, with user control access and different types of grants.

The platform stores measurements both from on-line and off-line sensors as well as laboratory analysis results. They are stored using a hierarchy of components: Company, Plant, Machine, Assembly, Sensor and Measurement.

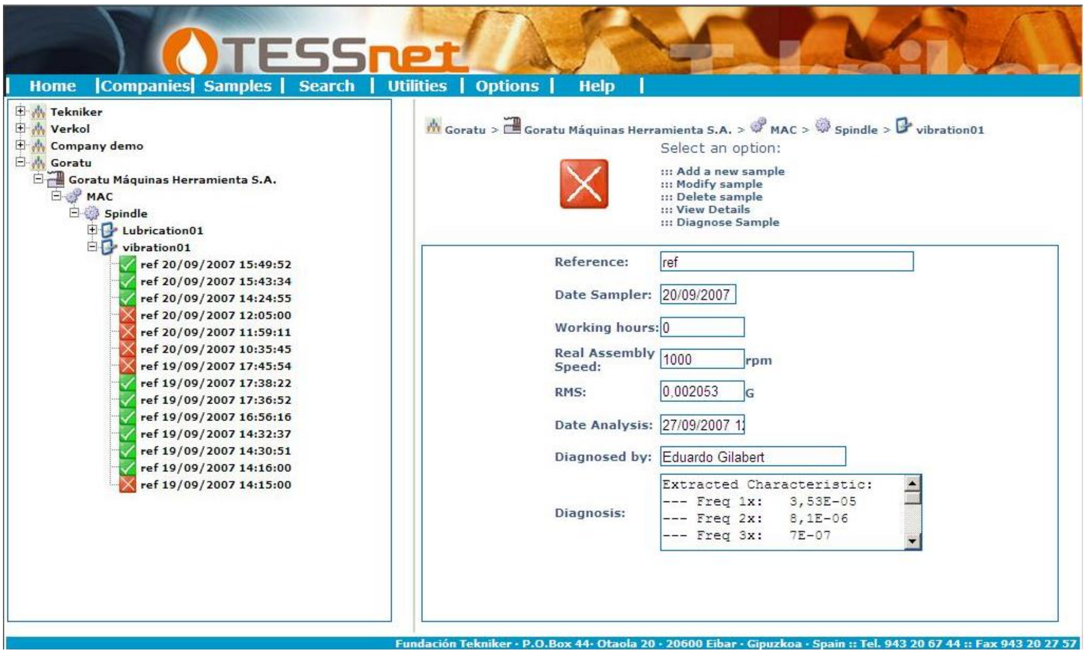

Figure 9. Vibration measurement in TESSnet

The intelligent system has been developed with .NET platform as a web application, using VB.NET programming language, and the database has been implemented with SQL server 2000.The advanced functionality of this platform is next described according to OSA-CBM Layers.

Condition monitoring

One of the web services of DYNAWeb used b TESSnet is devoted to perform condition monitoring tasks. The condition monitor receives data from the sensor modules, the signal processing modules and other condition monitors. Its primary focus is to compare data with expected values. The condition monitor should also be able to generate alerts based on preset operational limits.

The CM web service can analyse scalar data in four different forms:

1. Scalar values directly surpassing a direct static alert. Alert are defined by fixed limits.
2. Scalar values that surpass a static alert 'relative' to the original component status. Depending in deviation, an alert is issued associated to a specific severity.
3. Scalar that surpasses dynamic alerts, based on the trend of last sample values.
4. Scalar that surpasses a given alert when combined with another parameter.

The CM service will request alert values. In case of not provided, it can also request information concerning the specifics of the component (such as component type) and then look up for information concerning these specifics. In the end, the web service will return the type of Alert surpassed and the severity.

Health Assessment

The diagnosis or Health Assessment receives data from different condition monitors or from heath assessment modules. The primary focus of the health assessment web service is to prescribe if the health in the monitored component, sub-system or system has degraded. The health assessment layer should be able to generate diagnosis records and propose fault possibilities. The diagnosis should be based upon trends in the health history, operational status and loading and maintenance history.

The aim of this web service is to identify the type of problem related to an electro mechanical component. It can cope with many different symptoms and faults, which include unbalance, misalignment, gear and bearing related problems, etc. It also includes processing of information specifics of multi-speed machines (as in manufacturing systems). The web service can receive the following set of alarm types as part of the input configuration, according to measurements of vibration and oil.

Prognostics Assessment

The prognosis plans the health state of equipment into the future. TESSnet is able to estimates the remaining useful life (RUL) based on linear and exponential regression of measured values and the according alarm limit.

Furthermore, this information is very useful to set the right maintenance order list in scheduling task. The algorithm for the task arrangement takes into account the RUL of the machine, setting prior in time the maintenance tasks related to a machine with less RUL. It avoids the systematic application of corrective and preventive maintenance tasks, making this in a predictive way, with the main objective of performing a balanced maintenance with operational reliability.

This new type of maintenance pretends to achieve maximum resource optimization and operational availability minimizing cost with intelligent “decision support” based on an “operational support”.

7 Conclusions

This chapter has presented a flexible architecture concept named DynaWeb to provide flexible data and information management, where core concepts such as e-maintenance and OSA-CBM architecture are followed. The platform TESSnet interacts with intelligent web services implemented in DynaWeb. Taking advantages of this flexible architecture, a key diagnosis service has been also developed, explaining the process to create a Bayesian Network from the information available of a FMEA.

On the other hand, TESSnet platform has been introduced, a predictive maintenance management system, able to perform different types of tasks: Condition monitoring, Health assessment and Prognostics assessments. The main purpose is to achieve a flexible architecture concept to provide flexible data and information management, where core concepts such as e-maintenance and OSA-CBM architecture are followed. These services are accessible also as plug-ins through XML communication and MIMOSA data format, in order to achieve a more flexible and dynamic system, where any existing maintenance management system can query the services. So, these intelligent web services could be used in other applications in the same way than TESSnet.

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8.8 Use of probabilistic expert systems for application in maintenance & diagnosis. A technology to manage uncertainty and adaptation

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Resumen

Este artículo presenta una investigación que se centra en la extracción de modelos de diagnóstico genéricos para la detección de fallos. Por lo tanto, el énfasis está en el desarrollo de algoritmos inteligentes para ejecutar métodos de inferencia relacionados con la tarea de diagnóstico dentro del *condition monitoring*. Se presenta la búsqueda de una combinación adecuada de conocimiento de dominio actual en modelos de conocimiento genéricos, donde se seleccionan sistemas expertos probabilísticos, construidos con Redes Bayesianas (BN), como herramientas apropiadas. Además, se muestra cómo se puede adaptar BN y, por lo tanto, "aprender" nuevos conocimientos para hacer frente a los cambios que se aplican a la tarea de diagnóstico, como los cambios en maquinaria personalizada y sistemas de sensores, nuevas operaciones y condiciones ambientales.

Use of Probabilistic Expert Systems for application in maintenance and diagnosis. A technology to manage uncertainty and adaptation.

Aitor Arnaiz, Eduardo Gilabert (Spain)

Keywords: Bayesian networks, Knowledge modelling, Diagnosis, Uncertainty, Adaptation.

Abstract

Maintenance activities become more complex as more information is gathered, and higher performance and reliability levels are required, even in non-critical machinery, such as elevators and machine-tools. Given this, automated systems for maintenance decision support are increasingly needed. However, in order to effectively assess the status of any component, these systems must manage the uncertainty that bear the information and models. Also, systems should be able to cope with new component configurations and operating conditions.

This paper presents a research that focuses on the extraction of generic diagnostic models for fault detection. Thus, the stress is on the development of intelligent algorithms to execute inference methods concerning diagnosis task within condition monitoring. The search of an appropriate matching of current domain knowledge into generic knowledge models will be presented, where probabilistic expert systems, constructed with Bayesian Networks (BN), are selected as appropriate tools, where conditional dependencies between causes and events help to model the information contained in the domain. Also, it will be shown how BN can be adapted, and thus 'learn' new knowledge to cope with changes that apply to the diagnostic task, such as changes in customized machinery and sensor systems, new operation & environmental conditions, etc.

1. Introduction

This paper introduces the work carried out under a larger project (MINICON) that intends to develop a cost-effective integrated sensor processing units (SPUs) for inclusion of on-line condition monitoring systems on all range of industrial and civil machinery. This includes two goals: The consecution of a cost-effective hardware monitoring unit (or sensor processing unit-SPU) and the availability of automated systems to perform decision support on fault diagnosis and troubleshooting.

After a first sampling task on high-speed milling machines, a complete evaluation of the actual status of diagnostic systems has been made. As a result, Bayesian networks appear as a tool for the future for automated software systems handling the two most critical issues in diagnosis applications: Learning and uncertainty management. Here model development will be mostly based on the existence (or likely elicitation) of adequate domain knowledge, where examples play during model construction a complementary role on prototype validation, and where experience, or heuristic knowledge, is the primary source of information.

This paper summarises the work performed to construct a first model for uncertainty management [1]. It also includes a study of the different alternatives existing for learning (parametric vs. non-parametric, complete vs. incomplete, batch learning vs. adaptation) and the development of prototype systems that indicates how to handle adaptation in actual Bayesian network systems [2].

2. Revision of adaptation and uncertainty issues

Condition monitoring systems are a special sub-group of predictive maintenance methods that require great quantities of information in order to provide adequate response to different fault detection sub-problems: Identification of abnormalities, Diagnosis, Assessment of fault severity, Prediction on degradation, Prognosis, Troubleshooting. All these tasks are 'knowledge-intensive', as there is an evident need of expertise to be able to handle them. Also, the answer of previous problems requires the inclusion of information from many different sources (vibrations, temperature, oil, wear debris,…), sources that not very long ago were analyzed on isolation from each other.

Given this, it is highly desirable to have software intelligent enough as to perform above tasks. This can be of real benefit for novel users, as well as a valuable tool for experienced users in quickly analyzing large volumes of data [3]. However, knowledge in the area is still scattered, with well-known techniques (vibrations) and machinery (electrical motor), and other less well known (wear debris, oil analysis, machine-tools). In conclusion, we may define the domain knowledge as 'ill-structured' [4]. That is, there are different degrees of incompleteness and uncertainty in the causal relation that links the different input symptoms (Vibrations, Lubricants, Wear Debris) and fault characteristics (Location and type of failure, severity, remaining lifetime, …). There is also incompleteness of current knowledge, which is often difficult to complete because field information grows continually, mostly related to maintenance methods and historical records.

Finally, most existing software products only perform inferential steps. This is because learning -any change in diagnostic knowledge- is very difficult to be encoded, if possible at all. However, changes concerning most of the monitored machinery may appear everywhere, so ability to modify the diagnostic inferential steps is a must. In fact, learning abilities is really what makes us consider a system as 'intelligent'. It is not possible to consider a system as 'intelligent' when it keeps on making the same mistake over and over!.

The nature of knowledge to be learned

Given this into account, a real need of adaptation of condition-monitoring systems can be foreseen, given new working data that can be accessible through Internet, no matter where is data originated from. Once we suppose there exist knowledge for inference process of monitoring and diagnosis, we can investigate what learning features can be useful in these processes, in an ordered way [5].

We can first write down the different information chunks that can be available during the process. In this study, we could conclude on the existence of two main *knowledge sources*:

- Theoretical knowledge: Machinery design, mechanistic behavior in materials and components (bearings, gears...) for problems such as contamination and wear. We can include here heuristics (problem solving methods acquired through repeated experience by technical assistance, machinery users and third party consultants)
- Experimental knowledge: Data analysis gathered, diagnosis and troubleshooting actions performed.

Once we have a knowledge database, we can distinguish three basic motivations for learning and *knowledge change*:

- Correction of system errors
- Enhancement of knowledge base
- Improvement of knowledge base in terms of efficiency

Given this, there are different motivations for change on condition fault detection inference knowledge, where we can classify different learning activities as follows:

	Change foreseen	Data type	Knowledge source	Changes	Need
A	New knowledge due to new systems to maintain.	Theoretical	Manufacturer/ Third party provider (sensor)	Structure/ parametric	High
B	Calibration (Monitoring)	Experimental	Product provider.	Mostly parametric	Medium
C	Repair/Improvement on maintenance tasks	Theoretical /Experimental	Manufacturer	Parametric	High
D	Improvement on maintenance strategies	Experimental	Manufacturer	Parametric	Medium
E	Maintenance customization	Actor preferences	All	Parametric	Medium

Table 1. Summary of knowledge changes in maintenance tasks

Uncertainty management

Uncertainty appears in diagnosis problems at different levels, that can be classified as information and/or model flaws [6]. In a problem space as failure diagnosis by analysis of vibrations, we can see that, when talking about failure modes, the borderline between dissimilar problems is often fuzzy. For instance, it is difficult to determine if there is just misalignment or there is also unbalance. In many cases, even though it has a crystal clear difference, several issues complicate this:

- Machinery symptoms are likely to be a mix of different problems (Unbalance and misalignment appear very often, though one of them is at a minimal level)
- Information (e.g. spectra) could be unclear (frequency resolution is limited and, depending on the number of the components in analysis, and the spectral range, some measurements can be bond to more than one problem.
- In many cases, the range of the devices installed can limit information, such as the ability to measure the HFD and Spike energy measurements.
- Models also have inexactitudes, due to high human-dependency when assessing severity of spectra peaks. Concerning machine-tools, for instance, there is hardly no information about peak limits surpassed.

As a result, a given spectral patterns can be attached to several problems, with no certainty of exclusive interpretation (in almost all cases) and, therefore, uncertainty should be treated in order to solve diagnostic problems adequately.

3. Overview of bayesian networks

If we stress on the two problems described (uncertainty management and adaptation) we could find a knowledge modelling methodology that suits our aims: Bayesian Networks.

A Bayesian network is a model. It reflects the states of some part of a world that is being modelled and it describes how those states are related though conditional probabilities. All the possible states of the model represent all the possible worlds that can exist, that is, all the possible ways that the parts or states can be configured. A car engine can be running normally or giving trouble. It's tires can be inflated or flat. In medical diagnosis, the body can be sick or healthy,… In a causal system, some states will tend to occur more frequently when other states are present (If it is cloudy, the chances of rain are higher).

Bayesian networks are proving very useful because they are adaptable. It is possible to start with limited knowledge about a domain, and grow them as you know more about it. Furthermore, you can use as at any time the data available for inference, and the net will do as good a job as is possible with the available information. As a consequence, graphical probabilistic models, and more specifically Bayesian networks, are becoming popular.

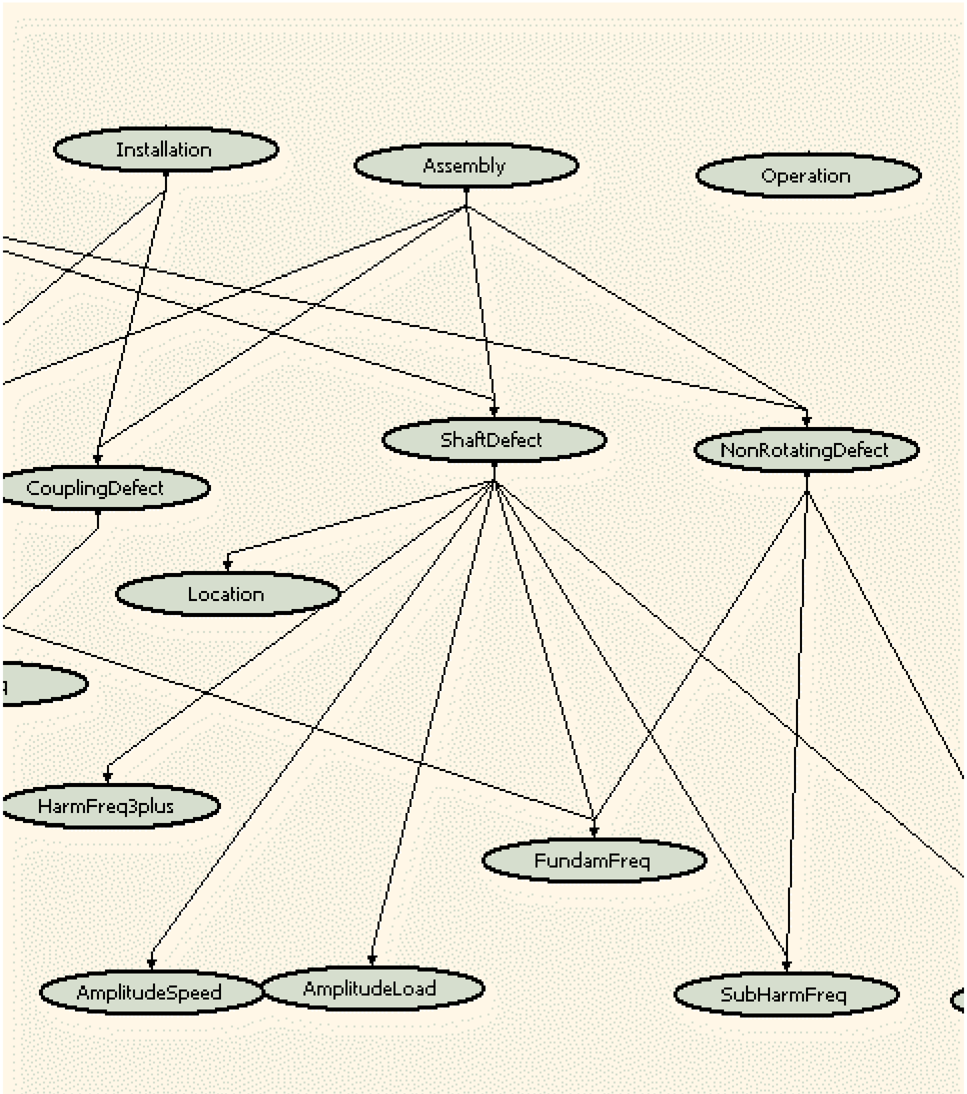

Figure 1. Excerpt of a machinery diagnosis graph model.

In the network prototype shown above, the qualitative relationship indicated by the direction of the link arrows corresponds to dependence and independence between events. That is the, nodes higher up in the diagram tend to influence those below rather than, or, at least, more so than the other way around. On the other hand, the quantitative relationships between nodes are defined by conditional probability tables (In case of continuous variables, conditional probability distributions)

In this case, we can also see that high vibration readings on spectral sub-harmonic frequencies can appear because of shaft defects rather than because of coupling defects. Also, we may conclude that the shaft defects can be most likely due to flaws in the assembly process than in other parts of the life-cycle product (such as design or operation). The causal links are complemented by adequate probability distributions, such as the table that appears below

Failure cause	*A priori*	Freq Probability			Meas. Probability		Amplitude incr.	
		1X	2X	>2X	Radial	Axial	Speed	Load
Unbalance	*40*	99			90	10	90	
Bent shaft	*10*	90	10		20	80	90	
Angular mis.	*30*	70	20	10	20	80		90
Parallel mis.	*30*	20	70	10	80	20		90
Mechanical loos.	*5*		80	20	90	10		
(Other causes)		*20*	*30*	*50*	*50*	*50*	*25*	*25*

Table 2. Excerpt from original chart of failure probabilities.

where it can be extracted that a-priori probabilities of having Unbalance are of 40%, and conditional probabilities of unbalance having evidence of high amplitude peaks at fundamental frequency (1X) are of 99%

That is. **P(+U) = .4** and **P(+U|+1X) = .99**

Basic aspects of Bayesian Networks

Many practical tasks can be reduced to the problem of classification. Fault diagnostics is one of these examples. A Bayesian network helps tackle the problem of classification in a way that helps to overcome problems that other methods partially address:

- Able to mix a-priory knowledge together with data/experimental knowledge
- Explanatory abilities
- Uncertainty management – Causality management
- Learning both parametric and structural issues.

Bayesian networks are a combination of two different mathematical areas: graph theory and probability theory [7, 8]. They can be defined as the representation of a *joint probability distribution* defined on a finite set of random variables, that can be discrete or continuous.

The representation is a directed acyclic graph (DAG) consisting of nodes, which correspond to random variables and arcs, which correspond to probabilistic dependencies between the variables. A conditional probability distribution is associated with each node and describes the dependency between the node and its parents.

The following diagram illustrates an example of a Bayesian Network.

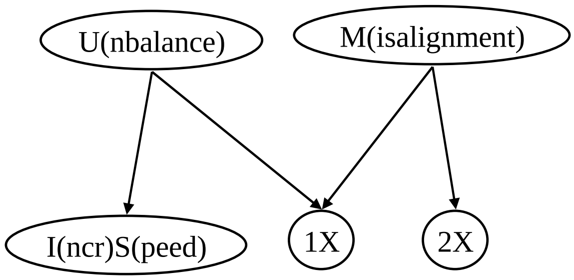

Figure 2. Graphical representation of a simple probability model

Here we can see a directed acyclic graph since each arc is directed and there are no loops. It contains 5 nodes (discrete random variables) that corresponds to different status that can occur in our system: *Unbalance(U), Misalignment(M), Amplitude increase in vibrations as speed increase (IS)*, *High amplitude peaks at fundamental frequency (1X)* and *High amplitude peaks at 2^{nd}. harmonic (2X)*. This graphical representation serves to represent the dependence and independence assumptions, that leads to develop a joint probability distribution. For instance we can say that 2X is conditionally dependent of M, but is conditionally independent of U given M.

That is $P(2X| U, M) = P(2X| M)$

We can also say that 1X and 2X are conditionally independent given Shaft Failure

That is $P(1X | M, 2X) = P(1X | M)$

Given this, we can see that the joint probability distribution is, in this case, reduced by factorization of the terms included into

$$P(U, M, IS, 1X, 2X) = P(U) \cdot P (M) \cdot P(1X| U, M) \cdot P(2X| M) \cdot P(IS| U) =$$
$$P(+U) \cdot P (+M) \cdot P(+1X| +U, +M) \cdot P(+2X| +M) \cdot P(+IS| +U) +$$
$$P(+U) \cdot P (+M) \cdot P(+1X| +U, +M) \cdot P(+2X| +M) \cdot P(+IS| -U) +$$
$$P(+U) \cdot P (+M) \cdot P(+1X| +U, +M) \cdot P(+2X| +M) \cdot P(-IS| +U) +$$
$$....$$
$$P(-U) \cdot P (-M) \cdot P(-1X| -U, -M) \cdot P(-2X|-M) \cdot P(-IS| -U).$$

Bayesian Networks as Probability Expert Systems

By probability theory, we know that we can infer many probabilities P(2X | M) = P(M) · P(M | 2X) / P(2X) by the use of Bayes theorem and conditional probabilities. This is used to infer the probability of Misalignment (M) having evidence on appearance of a peak of amplitude in 2^{nd} harmonic (2X), but it also can work in the opposite direction, making it useful –for instance- to reinforce other causes (such as Unbalance) if we already know that there is no Misalignment in the system. By the appropriate inference mechanisms, the management of the partial conditional distributions allows the calculation of probabilities for any node in the network given any evidence.

It turns out that the use of above descriptions of conditional probabilities and probability distributions where in use long before Bayesian Networks appeared. For instance, Prospector (Duda, 1980) was one of the first expert systems (or KBS) to use Bayes theorem for uncertainty management. However, probabilistic approaches were, at first, difficult to follow due to the difficulty in the definition/representation of joint probability distribution of several variables.

The solution came a decade ago through the development of net graphical probabilistic models (GPM), whose two main exponents were Hidden Markov Models and Bayesian Models [7], whose main characteristic was the association of graph models to conditional probability factors and the inclusion of appropriate algorithms to handle this distributions. In doing this, Bayesian networks develop an inferential process -probabilistic inference- that can be compared to that of old expert systems [8]:

- The knowledge base is made of facts in both cases, but instead of rules, probabilistic expert systems include conditional probability distributions
- The inference engine is now directed by the probability theory, that 'fires' the conditional probabilities by different algorithms that will normally provide approximate inferences.
- We can also see a parallelism between internal representations. If Rete algorithm was a breakthrough in terms of efficiency, the same can be said about junction trees, that paved the way for use of these systems.
- There is also parallelisms between explanation and learning mechanisms, only available as meta-rules in expert systems, and now much more powerful thanks to algorithms that interacts with conditional probabilities

What is more, the modeling of Bayesian Networks is completely suited to the new trends existing in knowledge engineering: The change from knowledge acquisition (represented by expert systems) to knowledge modeling. Both Bayesian Networks and knowledge modelling methodologies share the need of a proper knowledge representation through problem modelling within available templates and have arisen in last 10 years. In both cases, Knowledge Based systems can be seen as antecedents. Concerning this, Bayesian networks can be seen [9] as special knowledge representation systems fit for the representation of causal semantics.

4. Learning Bayesian networks

Learning a graphical model has become a very active research topic and many algorithms have been developed for it. Introductory and advanced information on probabilistic network learning can be found in [7]. Here, we can distinguish between many approaches: learning from adaptation or batch learning, where we can also divide between learning the whole structure of the network to form the model graph, or to just learn the information regarding the conditional distributions. There is also a big concern about learning from continuous variables, as well as to consider incomplete data problems - missing values and hidden (or latent) variables-. Two approaches are examined here for learning. The first one refers to adaptation. The second one refers to batch learning.

Adaptation. Fractional updating & Fading

Adaptation is the process of refining the (conditional) probabilities specified for a Bayesian network by taking into consideration the real experiment outcomes. This is probably the most interesting type of learning mechanism that can be used in machinery diagnosis, as the most important input (in learning terms) should be expected from local usage of the automated tools, as long as they start to be applied in maintenance and diagnosis systems. For example, every time a machine is diagnosed, the information about their symptoms and problems can be used to adapt the network's probabilities.

The simplest example is that referring to *fractional updating* tables, were an statistical task is meant to modify the estimates of the parameters gradually with the cases used. We can consider the CPT of Looseness, that is, the *prior* probability of having looseness in a given machinery type every time an abnormality is detecting

Looseness	
False	0.95
True	0.05

It is clear that this relationship may not reflect particular cases in different environments. For instance, a given company may present a particular highly rate of abnormalities related to this problem (Let say that 20% of problems corresponds to Looseness).

We can add a new feature on this Conditional Probability table, called 'experience', represented by a number that indicates the value that we assign to experience in the 'a-priori' design. Now, we can also include feedback from application of the system. For example, we can assume that our belief in the correctness of the current conditional distribution for looseness is low, thus we can set the initial experience count to a small number, say 10. Now, if we get feedback of 5 new cases (suppose that in all of them with found evidence on looseness) and go again to the CPT of looseness, we will see an experience value of 15. These additional 5 counts pertain all to state "true". Therefore, the adapted probability distribution of Looseness becomes

P(Looseness) = N(true)/(N(true)+N(false)) = 5.5/15 = 0.3666,

where N(True) indicates the number of true events recorded so far, which accounts for 5 in the last 5 observations, plus 0.5 in the first 10 observations (only a 0.05%), whereas N("false") accounts for the 95% of the original observations (That is, 9,5). This gives the following CPT as results is

Looseness	
False	0.6333
True	0.3666

To summarize, an adaptation step consists of entering evidence, propagating, and updating (adapting) the conditional probability tables and the experience tables. Of course, we can also add experience to conditional distributions (For instance, what is the real appearance of 2^{nd} harmonic peaks (2X) or greater if looseness appears).

The previous adaptation procedure gives equal weight to recent experiences and older ones. Sometimes, however, old observations do not count as much as more recent ones. Thus we have to *unlearn* or forget some of them. This is the same as saying that new observations (evidence) are more important than older, and hence should have more weight. Also, fractional updating has a problem of overestimation of counts importance, so that counts can make parameters in CPT too resistant to change.

Such situations can be overcame by fading tables, which accounts for the rate at which previous observations are forgotten. Thus, with an intermediate fading value of 0,5 and 12 single new true case of looseness:
N(True) = fading_factor * N(previous_true) +1 = 0.5 * (0.05 *10)+ 1 = 1.25
N(False) = fading_factor * N(previous_false) +1 = 0.5 * (0.95 * 10) = 4.75
N(True) + N(False) = 1.25 + 4.75 (That is: Experience is now counting only 6, instead of initial 10, or instead of 11, if no fading exists)

Given, this, the updating with just 1 new positive observation of looseness is P(true) = 1,25/6 = 0.21 (aprox). A very significant change with just one observation.

Batch learning

Batch learning can be referred as automatic model induction from samples, and actually has a significance closer to data mining supervised classification techniques. However, it is also possible to retrain/rebuild a network from scratch with available information that can serve to improve automatically. This is useful if new options enter into the system, such as new machinery types or new monitoring techniques are to be considered. This needs a much greater sample/cases size than in previous approach, but still limited -when compared to ANN, for instance- since it is no need of splitting the sample size between training and testing. When sample set exists, it is possible to use several approaches to learn quantitative and even qualitative aspects of a Bayesian network.

The qualitative methods are referred to as structural learning or model selection, whereas the quantitative ones are parameter learning or parameter estimation algorithms. This is a very hot topic still under research [10, 11]. Parameter estimation uses algorithms such as EM (Estimation-Maximization) to look for the best parameter distribution given a a-priori graph configuration. Methods for structural learning includes Naïve Bayes approaches, search & scoring based methods (K2) and dependency analysis (PC, NPC). Some of these methods (EM) are already eligible, tough structural learning methods can only be considered as promising.

5. Conclusions

This paper has presented an outline of Bayesian Network basics, with partial examples of an application for diagnosis of mechanical faults. We have pointed out the convenience of Bayesian Networks as algorithms for automated diagnosis in uncertainty management scenarios. A complete diagnostic system has been developed using MSBNx tool[12], and embedded into a general condition monitoring system developed in Tekniker [13]. The testing of the inferential system has been made with data extracted from machine-tool high-speed spindle heads.

This paper also presents an outline of available learning algorithms within Bayesian Networks. The complete deployment and testing of learning capabilities is being made with HUGIN tool [14], which includes the necessary algorithms to implement the learning system. Learning can be considered as the true characteristic that makes a system to look like an intelligent device, automatically preventing the repetitive occurrence of silly errors.

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8.9 Condition Based Maintenance for Sustainability

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- **Editora:** Springer
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Resumen

Este documento aborda la necesidad de desarrollar estrategias sostenibles aprovechando las plataformas electrónicas que brindan soluciones avanzadas de gestión del mantenimiento. Las estrategias de mantenimiento basadas en la condición pueden facilitar la incorporación de estrategias relacionadas con la sostenibilidad de una manera eficaz y eficiente. El documento también muestra una plataforma electrónica basada en las tecnologías de mantenimiento actuales ya desarrolladas, junto con estrategias para seleccionar la ruta más rentable en la búsqueda de una estrategia de excelencia de mantenimiento. La consecuencia es la posibilidad de presentar e integrar las últimas tecnologías de mantenimiento electrónico en sistemas de gestión de la energía eficientes que pueden beneficiarse de la gestión conjunta de los aspectos de mantenimiento y eficiencia energética dentro de la industria de fabricación.

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CONDITION BASED MAINTENANCE FOR SUSTAINABILITY

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This paper addresses the need of developing sustainable strategies by taking advantage of e-platforms bringing advanced maintenance management solutions. Even tough most maintenance systems are cost oriented, it is also clear that new factors are gaining weight when considering strategies and operation, like safety or environmental issues. On the other hand, Condition-based maintenance policies may facilitate the incorporation of sustainable-related policies in an effective and efficient way. Condition monitoring may extend the control focus to all areas where maintenance performance losses occur and therefore support the development of sustainable maintenance strategies related to direct economical cost but also to indirect costs such as energy efficiency or material waste. The paper also shows an e-platform based on current maintenance technologies already developed, together with strategies to select the most cost-efficient path in the search for a maintenance 'excellence' strategy. The consequence is the possibility to bring forward and to integrate the latest e-maintenance technologies into efficient EMS (Energy management Systems) that can benefit of the joint management of maintenance and energy efficiency aspects within manufacturing industries. In particular, the approach relates to energy efficiency as a principled way to advance in sustainability, through specific energy-efficiency indicators and operating systems (i.e. integration of sensors and decision-making algorithms) that stresses the importance of energy-efficient optimization in manufacturing.

Key Words: Condition Based Maintenance, e-Maintenance, Sustainability, Energy Efficiency.

1 INTRODUCTION

The manufacturing Industry within Europe is driven by economic incentives, particularly in the context of the recent world recession, to implement significant energy efficient improvements in its processes and the equipment it uses (electric motors, compressors, etc.). European and national legislation impacts on the energy consumption and in that connection industry must also take the necessary measures to fulfil the gap on energy consumption limitations imposed by European and National legislation and on greenhouse gas emissions imposed by the National Allocation Plans as foreseen in the Emissions Trading Directive. In addition, companies are under pressure to respond to rising energy costs and the need to protect the environment. Growth in energy consumption has a direct impact on the deterioration of the environment and on climate change. Air quality is a major environmental concern for the EU. The Commission is currently elaborating the EU Clean Air Programme (CAFE), where the harmful effects of ozone and especially particulates are revealed for human health and ecosystems.

Given this, it is important to focus on the need of developing sustainable and energy efficient manufacturing strategies through the research, development a demonstration of novel methodologies and technologies allowing the improvement of environmental, economic and social policies. In this sense, maintenance is crucial to manufacturing operations. In many firms the facilities and the production equipment represent the majority of invested capital, and deterioration of these facilities and equipment increases production costs, reduces product quality and has a significant impact on energy consumption. Over recent years, the importance of maintenance, and therefore maintenance management within European manufacturing organisations has grown [1,2].

On the other hand, European manufacturers have introduced a variety of innovative technologies, new business processes and enlightened management techniques to encourage greater efficiency in the industrial use of energy. However, equipment maintenance has been overlooked and falls short with regard to the development of innovate and new technologies to monitor energy efficiency, emissions, and other environmental issues. In this respect, the most important barrier to increase energy efficiency is a lack of information (on costs and availability of new technology; on costs of own energy consumption decrease;

on financial impact on the rate of return from investment.) as well as lack of training and awareness of technicians on the effectiveness of proper maintenance using the latest technologies.

2 LIFE CYCLE ASSESSMENT

Over the past decade, plant maintenance has evolved to be one of the most important areas within manufacturing organisations, large or small. The success and sustainability of any energy intensive industry is measured by their ability to perform well with regard to certain criteria such as cost, quality, delivery, dependability, innovation and flexibility. In order to achieve and maintain these criterions these organisations are undertaking efforts to improve quality and productivity and reduce manufacturing costs by examining the activities of the maintenance function. Effective maintenance is critical because the goal is to extend equipment life, improve equipment availability and retain equipment in a clean, reliable, safe, and energy efficient condition. Customers demand ever-increasing reliability, with faster lead and delivery times.

Existing strategies seek for optimized operational solutions involving maintenance and operational costs, energy efficiency and CO2 emissions. On the other hand, the European Union set itself ambitious targets by the year 2020 (to reduce the output of greenhouse gases by 20%, to improve energy efficiency by 20% and to increase the percentage of renewable energy by 20%).

Even though many tools for the assessment of environmental impacts are available, such as Life Cycle Assessment, Material Flow Analysis (MFA), and Environmental Impact Assessment (EIA), Life cycle assessment is the most widely used technique and allows organisations to identify the strong correlation between energy efficient maintenance and productivity. Using LCA when making purchasing and maintenance decisions ensures that all benefits are taken into account.

In adequate conditions, the LCA methodology enables to assist an effective integration of the environmental considerations in the decision-making process. The Life Cycle Assessment (LCA) and Life Cycle Cost (LCC) concepts are directly related to the sustainability of the manufacturing and maintenance processes [3]. The objective of use LCA and LCC is twofold. On one hand, LCA model is able to analyse the complex interaction between the product and manufacturing process and the environment, considering the energy efficiency, from cradle to grave, while the LCC can analyse the total “lifetime” cost to purchase, install, operate, maintain, and dispose of the products.

Using LCA would result in a more realistic, integrated, and accurate view of the potential optimisation of a production line. In addition it would be very useful in assisting the whole product development by identifying more sustainable options in process selection, design and optimisation, and in particular the energy efficiency and CO_2 emissions. Therefore, LCA as analytical tool allows the assessment and simulation of the environmental impacts that different operational decisions, as well as monitoring technologies [4], have on the whole life cycle of the manufacturing plant.

The EU-founded collective research project PROLIMA (Environmental Product Lifecycle Management for Building Competitive Machine Tools) was developed focusing on the sustainability of the European producers of machine tools, which try to increase the competitiveness based on quality, value for money and low environmental impact. PROLIMA Sustainable Machine Tool Design Methodology ($SMTD^M$) aims to provide a global methodology for sustainable design, manufacturing, operation and maintenance considering the economical, environmental and social issues.

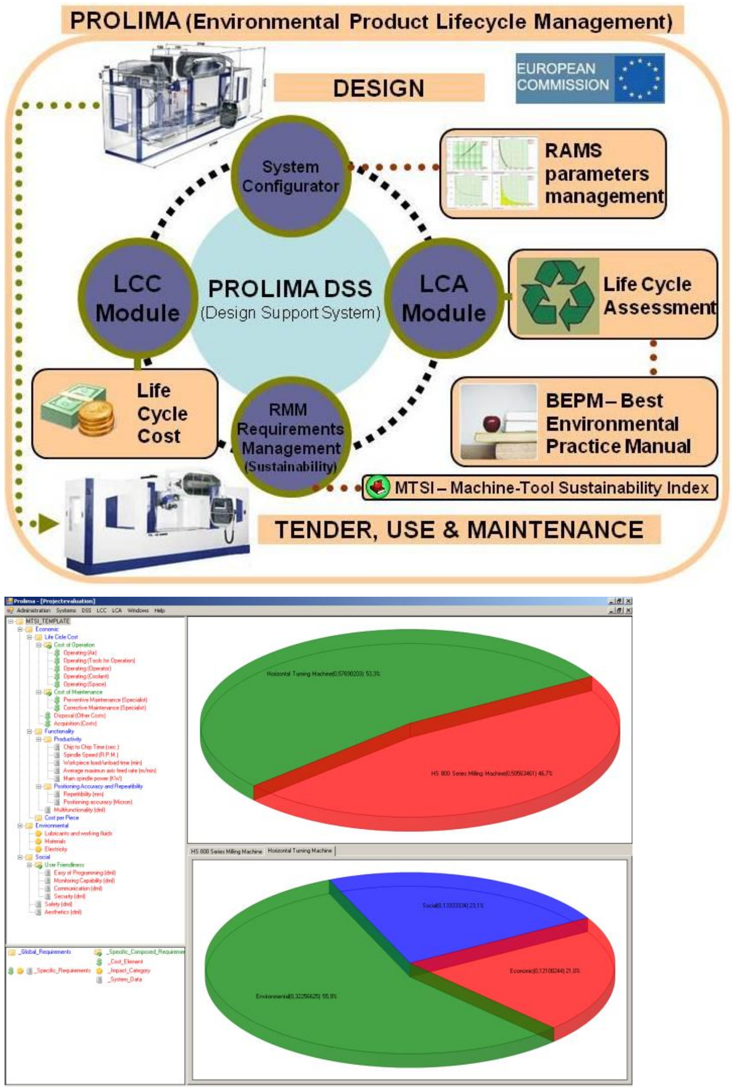

Figure 1. PROLIMA concept

PROLIMA's core is their Decision Support System (DSS) which integrates the information of the Life Cycle Cost (LCC) tool and the Life Cycle Assessment (LCA) tool, together with Social aspects (safety, ergonomics, aesthetics, usability, …) and functional aspects (productivity, precision, cost per piece, etc). Requirements models can be customized to each kind of product according the characteristics of the manufacturer and the customer. As an example, Machine Tool Sustainability Index (MTSI) was developed for machine tool sector. According to these models, designers can evaluate the Sustainability Index of different configurations from early design stages, when most of critical decisions are made and main costs are committed. Using an appropriate methodology supported by useful tools give the pragmatic guidance to choose the best ecodesign considering manifold points of view over the product life span.

3 SUSTAINABLE E-MAINTENANCE PLATFORM

The integration of novel joint LCA/LCC/RAMS analysis tools can be used for simulation and evaluation purposes for the new advanced maintenance techniques and technologies. The recently finished EU-funded Integrated Project DYNAMITE (Dynamic Decisions in Maintenance) has been to bring together a group of technologies that can be integrated in a structured way, yet flexible enough to allow the selection of a particular subset of the technologies. The main idea behind the platform is a series of "plug and play" hardware and software components that can be included on demand in any existing use case, without a need to remove any legacy system. The growth of wireless communication technology, mobile technology and web technology have allowed maintenance strategies to be developed using accurate information collect using sophisticated technologies [5,6]. Technological developments in e-maintenance systems, radio-frequency identification (RFID) and personal digital assistant (PDA) have proven to satisfy the increasing demand for improved machinery reliability, efficiency and safety [7]. Maintenance task selection are now developed by applying a blend of leading-edge communications and sensor technology including Radio Frequency Identification (RFID) and Personal Digital Assistant (PDA) to enhance diagnostic and prognostic capabilities [8][9][10].

The figure below provides a schematic overview of the complete system concept depicted for information and communication technologies that summarises the e-platform concept. This view identifies the existence of three layers (squared on the right of the figure) with the location of several actors (maintenance and operation operators) with respect to the company, and also stating the interoperability of these actors with different technologies.

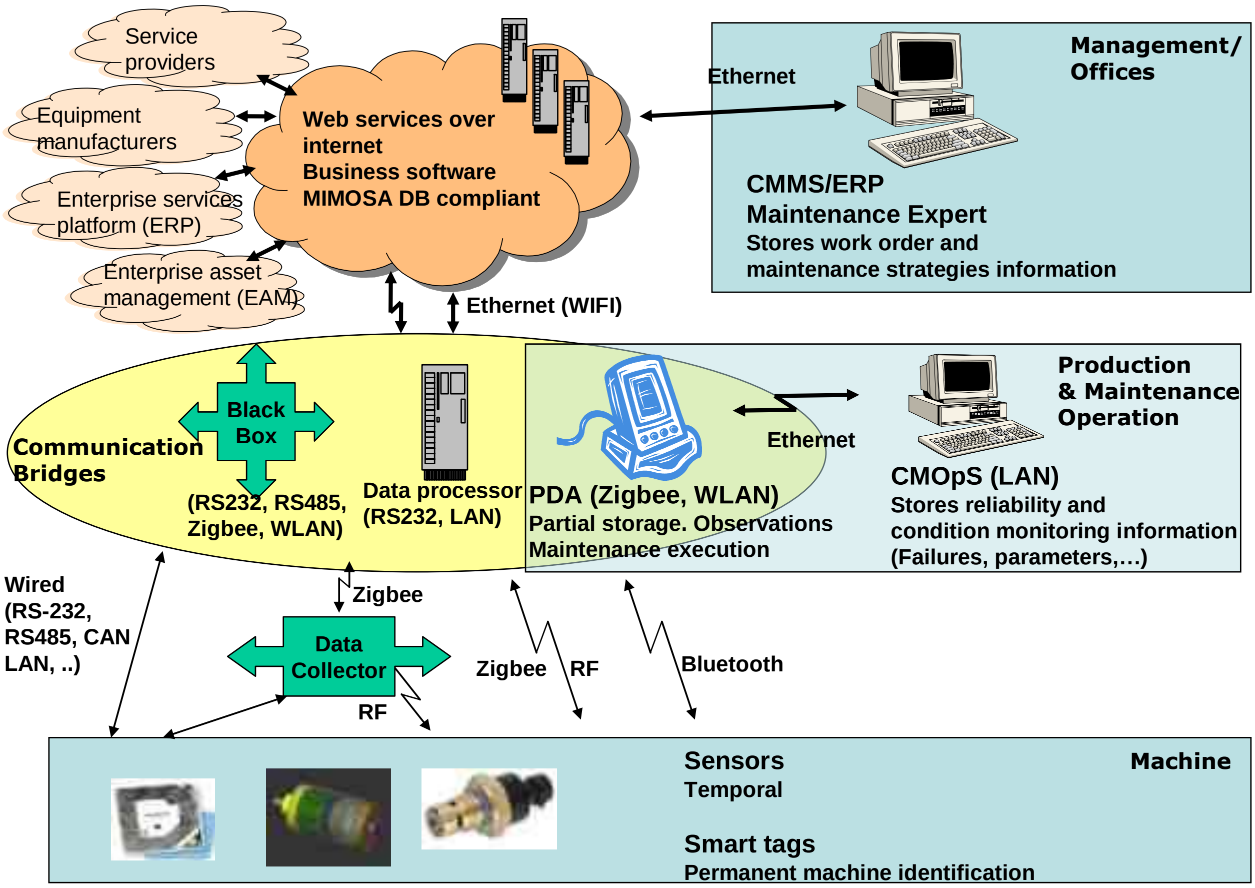

Figure 2. An example of ICT structure (Dynamite project)

The first level corresponds to the machine and identifies sensors and smart tags as associated to this level of interoperation. It is also expected that sensors hold temporal information concerning current condition values, with little or no historical information attached. The second level corresponds to the production shop floor and identifies two main actors: The personal digital assistant (PDA) and the Computer and Maintenance Operational support (CMOpS). It is argued that these can both hold temporal information concerning operator activities and input values, and that CMOpS will hold historical records on selected condition information. The third level corresponds to headquarters and management staff, where both tactical and strategic decisions are made. CMMS as well as maintenance expert agents are located at this level, together with information concerning scheduled operations and maintenance strategies [11].

In this sense, it is important to insist on the distributed nature of the platform, which facilitate the inclusion of new modules (i.e. metering devices for energy-efficiency indicators, novel and existing algorithms for EMS decision-support). This maintenance operating platform should be also combined innovative energy data Smart Metering systems have been developed. This innovative approach to energy metering allows for two-way communication between the utility (supplier or DSO -Distribution System Operator-) and the meter. “Smart meters are modern, innovative electronic devices capable of a wide range of useful information, enabling the introduction of new energy services. Smart Metering systems consist of several different technical components which include the following functions:

- Accurate measurement of electricity, gas, water or heat usage
- A data transmission infrastructure
- An IT environment suited to the ensuing data volumes

- A consumer-oriented invoice system
- Local display of energy usage data

In spite of their applicability, Smart Metering systems have not been widely used within any sector across Europe. This lack of usage may be due to the unavailability of low level Energy Management Systems (EMS), capable of monitoring the energy consumption, as SCADA-like systems. Current target aims to integrate these Smart systems within the e-platform, providing an efficient Operational Management System, including current EMS functionality within a more complete manufacturing management system that will

- Store and analyse data collected by maintenance engineers and equipment operators (Dynamite technologies)
- Store energy consumption data and use real time technologies to constantly update cost of energy. This is based upon sub-metering equipment installed on key items
- Provide maintenance tasks via "intelligent software" to maintenance engineers/equipment operators via portable devices.
- Use wireless technologies to update maintenance tasks planned/unplanned and provide energy consumption data
- Provide management with true cost of maintenance including energy cost and cost of spare parts, etc.

This software will help industry to monitor, manage and optimize their energy usage for maximum efficiency and cost savings. In addition the software would include reporting and analysis tools that evaluate the energy use patterns of all processes and pinpoint areas for improvement. Finally it would be able to coordinate electricity costs to provide a true cost. And with LCA/LCC analysis tools we will evaluate the best strategy for the sustainable and cost-effective manufacturing plant.

4 CONCLUSIONS

The need of developing sustainable strategies by taking advantage of e-platforms bringing advanced maintenance management solutions has been addressed. New factors as safety or environment issues are gaining weigth in maintenance systems. Condition monitoring may extend the control focus to all areas where maintenance performance losses occur and therefore support the development of sustainable maintenance strategies related to direct economical cost but also to indirect costs such as energy efficiency or material waste. The paper also shows an e-platform based on current maintenance technologies already developed, together with strategies to select the most cost-efficient path in the search for a maintenance 'excellence' strategy. The consequence is the possibility to bring forward and to integrate the latest e-maintenance technologies into efficient EMS (Energy management Systems) that can benefit of the joint management of maintenance and energy efficiency aspects within manufacturing industries. This approach relates to energy efficiency as a principled way to advance in sustainability, through specific energy-efficiency indicators and operating systems (i.e. integration of sensors and decision-making algorithms) that stresses the importance of energy-efficient optimization in manufacturing.

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8.10 A standard-based data model for configuration management and maintenance support

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Resumen

Esta contribución define un modelo de datos para la gestión de la configuración y el mantenimiento, teniendo en cuenta todo el ciclo de vida de los activos. Esta definición se basa en la revisión de los sistemas relacionados con la gestión de la configuración, verificando el uso de estándares y normas, y examinando cómo se complementan. La definición de modelo de datos se presenta organizada en 7 capas de información y se aplica en un caso de uso.

A standard-based data model for configuration management and maintenance support

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Abstract: The goal of this paper is to define a data model for configuration management and maintenance, taking into account the whole life cycle of assets. First step was to review the systems related to configuration management checking the utilization of standards and norms which are connected in a practical way, and looking for the relationship of the different possible data models used for configuration management systems. A definition of data model is presented organized in 9 layers of information and it is applied in an use case where is checked the problems of the data model with the purpose of improve it.

Keywords: Configuration Management, Maintenance, data model, MIMOSA

1. THE CONFIGURATION MANAGEMENT

Configuration management (CM) is the process to identify the physical and functional characteristics of a configuration item (CI) during all life cycle (software, firmware or hardware), controlling all characteristic changes, recording and processing changes reports, and controlling the implementation status.

The configuration management consists of 4 basic functions (Buckley 93) (Bounds 93):

1. Configuration identification: Physical and functional characteristic identification of a CI in any phase of whole life cycle. It includes a formal CI selection and documents conservation of the CI base where all the system is identified and defined.

2. Configuration control: Systematic request, justification, evaluation, coordination, approval, or disapproval of proposed modifications and the implementation of changes in the configuration of each CI, as well as in the documentation where is identified the configuration of each CI

3. Configuration status accounting: Recording and reporting the implementation of all modifications of the configuration and identification documents.

4. Configuration audit: Asses the compliance of the CI with the configuration identification

The core purpose of CM is to allow for better decision making, on products, projects and programs, in order to control changes through the creation and maintenance of documentation and products with the ability to reference this data at any time.

In this context, Configuration management leads to a more effective maintenance. For example, it is possible to have a better traceability of equipment, having in mind all the changes that the equipment has; improve maintenance logistics knowing the actual configuration of an asset; or comparing between two machines configuration to select the best one for the company.

The CM is mainly supported by the data model employed. There are several standards for configuration management o maintenance performance, but not any previous work has been carried out trying to integrate a configuration management data model in the field of maintenance. For this reason we have considered the need to define a data model in a broad way, taking into account aspects related to maintenance performance, logistics, costs, condition and reliability, join to configuration identification and control.

2. STANDARDS REVIEW

Having in mind this definition, current standards, norms and guides, applications or products of different sectors, patents, and benchmark companies and universities have been studied to define a data model for configuration management as a support for operation and maintenance.

A set of different standards covering full life cycle spectrum were reviewed and used. The standards and guidelines considered are listed in Table 1.

2.1 ISO 10303 Standard for Exchange of Product model data (STEP)

STEP is a standard which deals with product structure, geometry and part-related information (Rachuri 2006). It is quite complex and composed by many parts. It has been approved as an international set of standards since 1994. The main drawback of STEP is that manufacturers and software developers perceive it as an expensive solution, despite it has been proven to save efficiencies in time, material and staff.

Table 1. Summary of standards related to CM and maintenance

Standard	Description	Data model
ISO 10303	Data standard for a product model	Guides for product data, geometry, part-related information
GEIA 927	Common data schema for complex systems	Guides for product, physical and functional system architecture during life cycle.
ANSI/EIA 836	Interchange of data for configuration mangement	XML schemas supporting CM
ANSI/EIA 649	Configuration management in a general way	Guides for configuration management
MIMOSA OSA-EAI	Architecture for the activities of Operation & Maintenance	XML schemas and a data base for supporting maintenance, condition monitoring, operation and reliability
ASD/AIA S1000D	Specifications for technical publications	XML schemas and a database supporting information types as descriptive, procedural, maintenance schedules, fault isolation and crew/operators
PAS 55	British standard for asset management	Guides for resources managemet, cost-benefit analiysis, risks and life cycle.
IEC 60300	Dependability management and life cycle costing	Guides for Dependability and Life Cycle Costing

2.2 GEIA 927 Common data schema for complex systems

The Government Electronics & Information Technology Association (GEIA) is an ANSI standard which supports its electronic and IT membership. It became a standard in 2006 and is in continuous improvement. Their main target is to provide a unified schema that integrates the best available schemas for data representation for modern complex systems during their whole life cycle, including next phases: system engineering, feasibility assessment, requirement definition, domain engineering, system realization, system operation, system support, system maintenance and the decommissioning of the system (Colson 2006).

2.3 ANSI/EIA-836 Configuration management data exchange and interoperability.

GEIA launched in 2000 a standardization project in partnership with the Department of Defense of U.S.A. and several industry participants, whose target was to develop a new CM data exchange and interoperability standard (EIA 2010). The standard ANSI/EIA-836 was proposed, which includes a CM data element dictionary and reference schema, and a set of XML schemas and templates (eXtensible Markup Language) for CM business objects. The usage of XML enables easy interoperability or data exchange among different systems.

2.4 ANSI/EIA-649National consensus standard for configuration management.

The target of standard ANSI/EIA-649 is to provide CM principles that are applicable o a broad range of different industries. This standard describes the functions and principles of CM in a neutral terminology for use with any product line. The standard describes next functions: CM planning, configuration identification, configuration change management, configuration status accounting, and configuration verification (EIA 2011).

2.5 MIMOSA standards

MIMOSA standards (Machinery Information Management Open Systems Alliance) allow the collaboration in the asset life cycle management, in commercial and military applications. We could affirm that they enables an e-maintenance infrastructure, that is, a network which integrates and synchronize different applications in maintenance and reliability for compiling and distributing asset information, what you need, when you need. One of main benefits of these open standards is that allow access to several information types.

OSA-CBM standard (Open System Architecture for Condition-Based Maintenance) is an architecture for monitoring and diagnosing assets. It integrates all CBM process, from data acquisition to decision support. OSA-CBM defines 6 functional blocks for CBM systems (Data Acquisition, Data Manipulation, Condition Monitoring, Health Assessment, Prognostics and Decision Making) and the interfaces among these blocks.

OSA-CBM is based on OSA-EAI specifications, using CRIS as core infrastructure (Common Relational Information Schema). CRIS model represents a static data view produced by a CBM system. It allow communication among diagnosis, health and prognostics, maintenance model, work orders, providing the required framework for storing reliability information, CRIS is adapted to XML.

Due to the existence of lot asset management systems, the integration process can be very difficult since they have their own interfaces for data exchange. For this reason, OSA-EAI standard (Open System Architecture for Enterprise Application Integration) was developed by MIMOSA in order to provide a standard for interoperability in asset management (Mathew 2009). OSA-EAI is a open standard for data exchange in different key areas inside the asset management, like identifications, task managements, setting diagnosis and prediction, vibration and acoustic data, lubrication, fluids and gases, thermography and reliability information. The interfaces among these areas are defined through XML schemas. Comparing to OSA-CBM, OSA-EAI provides the data architecture for storing data, that is, a database.

2.6 ASD/AIA-S1000D

S1000D is an international specification for technical publications, developed by the European Association of Aerospace Industries (AECMA). The employment of this standard should handle a wide range of information types such as descriptive, procedural, maintenance, schedules, fault isolation, and crew/operators. It used international standards as Standard Generalized Markup Language, XML and Computer Graphics Metafile for the production and use of electronic information.

S1000D has been defined in a modular approach, defining data module as a "self contained unit of data" and having 2 main sections: one containing required data by the user (content section) and the other one containing metadata needed for controlling the module and configuration (identification and status section). Any shared information is stored once in a database and a used many times in different context by means if an identification code for the module.

2.7 PAS 55

The Publicly Available Specification (PAS) was published in 2004 in response to growing demand of industry of an asset management standard (Bsi 2008). It provides a definition of 28 specifications to implement and audit an integrated and optimized system taking into account the whole life cycle of physical assets.

Asset Management is defined as "systematic and coordinated activities and practices through which an organization optimally and sustainably manages its assets and asset systems, their associated performance, risks and expenditures over their life cycles for the purpose of achieving its organizational strategic plan".

A management system is the way that practices of a company are specified and controlled with the aim of enabling organizational plans, based normally in the quality cycle (Plan, Do, Check and Act).

BSI PAS 55:2008 establishes how, in an audible way, corporate management plans are obtained, aligning policies, strategies, objectives and finally plans with specific actions for people with the required competencies, responsibilities and authority. This way the asset management system is a mechanism to assure that total planning during whole life cycle, risk management, cost/benefit, customer approach, sustainability, etc. principles are implemented in day-to-day work.

2.7 IEC 60300

The International Electrotechnical Commission (IEC) is a worldwide organization for standardization. The object of IEC is to promote international co-operation on all questions concerning standardization in the electrical and electronic fields (IEC 2004).

IEC 60300 Deals with dependability performance issues including availability performance, reliability performance, maintainability performance, and maintenance support performance. In particular, IEC 60300-3 Section 3 is an application guide for life cycle costing. It explains the purpose and value of LCC and outlines the general approaches involved. Moreover, it identifies typical LCC elements to facilitate project and program planning.

3. DATA MODEL

Once all standards were reviewed, the next step was to study how they could be combined to obtain an easier way of working with them. In this way, the solution is a data model based on the standards and structured in 9 layers according to different views of the asset:

- Configuration identification: Physical or functional identification of the hardware or software in whole life cycle.
- Record of asset changes: Modification recording of the asset configuration
- Location: Asset location related information
- Maintenance performance: Sequence of steps to complete a maintenance task.
- Maintenance Logistic: Tools, materials and staff to complete maintenance tasks and their location.
- Maintenance policy: Asset applied maintenance policy or strategy. Corrective, preventive, predictive and related information.
- Costs: Maintenance, reparation and spare parts costs related information.
- Condition: Asset health condition, health prediction, sensing, measurements and inspections.
- Reliability: Historic data of completed maintenance tasks, design reliability data, and failures.

Before defining the content of every layer, has been selected the standard associated to them, as detailed in Table 2.

Table 2. Data layers and related standards

Data layer	Norms /Standards
Configuration identification	ISO 10303 GEIA-927 EIA-836 EIA-649 OSA-EAI
Record of redesigns	ISO 10303 GEIA-927 EIA-836 EIA-649
Location	MIMOSA OSA-EAI
Maintenance performance	ASD/AIA-S1000D MIMOSA OSA-EAI
Maintenance Logistic	ASD/AIA-S1000D MIMOSA OSA-EAI
Maintenance policy	PAS 55 IEC 60300
Condition	ASD/AIA-S1000D MIMOSA OSA-EAI
Costs	PAS 55 IEC 60300
Reliability	MIMOSA OSA-EAI PAS 55 IEC 60300

MIMOSA OSA-EAI is assigned in most of data layers, making it the most suitable standard in a wide perspective. In this sense, could be coherent to select OSA-EAI as our standard for configuration management and maintenance data model. But this selection has several inconveniences. First, it is focused more in the communication between different applications than integration different types of data in a unique data model. For this reason, this database is composed by hundreds of tables, making it difficult to use and keeps up to date. Moreover, OSA-EAI does support neither configuration management nor life cycle costs.

Taking into account that, OSA-EAI can be used as a starting point in our data model, but requiring a simplification to be more operative, and an integration of other standards covering their gaps.

Therefore, our first data model is composed by the conjunction of 3 standards:

- MIMOSA OSA-EAI: selected standard for configuration identification, asset location, maintenance performance, logistic and policy, condition and reliability.
- EIA-836: Selected standard for recording the asset changes. This standard also provides a database definition, making easier their integration with OSA-EAI.
- IEC 60300: standard providing a cost model based on Life Cycle Costing

4. APPLYING THE DATA MODEL AND RESTRICTIONS FOUND

Applying this schema in a bus fleet company, data model features are reviewed, and some none easily and universally solvable restrictions appear for the different data models.

When our data model has been applied in the use case, the main objective was to have an easier information management and treatment, instead of having a “perfect” model. Starting from these restrictions, and with a practical view of the tests, the data model has been adjusted, in order to obtain a new conceptual model, more agile for future system users, and as a consequence it will be less costly to maintain.

On the one hand, 3 layers, maintenance performance, policies and logistics have been integrated in a unique layer due to the relative simplicity of logistics and policies layers. On the other hand, several object definitions has been removed from our data model for not proving any relevant information, and others has been classes are grouped or converted into other object associated parameters. In Table 3 is detailed the changes performed in the new 7 layers.

Table 3. Changes performed to data model

Data layer	Changes performed
Configuration	Class elimination of Database in OSA-EAI
Historic of redesigns	Structure simplification of EIA-836B:. Class conversion to properties: Date, Authorized by, Description, Modification description, conducted tests.
Location	OSA-EAI standard: Modifications in the definition of the position class “Map” and simplification of the GPS definition
Performance and logistic	OSA-EAI distinguishes between events of Assets and Segments. Structure simplification, without the duplicity. Class “Audit” elimination
Costs	No restrictions
Condition	OSA-EAI condition structure assigned to Segment. Modifications in the structure, more flexible for Assets and Segments
Reliability	OSA-EAI has duplicity in the structure for Assets and Segments. Structure simplification and removal.

4. FINAL DATA MODEL

Finally, a conceptual data model is defined with the required changes to avoid the described restrictions for future system users. In Table 4 is summarised the new conceptual data model, indicating the main objects in every proposed layer.

Table 4. Final data model

Data layer	Description	Objects
Configuration	Physical or functional identification of the hardware or software in whole life cycle	Enterprise, Site, Asset, Segment, Asset_type, Segment_type, Agent, Manufacturer, Model
Historic of redesigns	Modification recording of the asset configuration	Asset, Segment, Change_done. Agent, Change_Replacement, change_Add, Change_Modification ,Change_Removed
Location	Asset location related information	Asset, Segment, Agent, Position, Direction, GPS, Asset_Position, Segment_Position, Agent_Position
Performance and logistic	Step sequence to perform a maintenance task, tools, materials and people required to perform the maintenance and their location	Asset, Segment, Event, Recomendation, Work_request, Work_order, Operation, Defect, Tool, placement, documentation, Agent, Subcontraction, Order_completed, Cause, Action
Costs	Maintenance costs, repair and spare parts. Maintenance strategies applied to asset, corrective, preventive , predictive and other information	Asset, Segment, DesingManufacturingCosts, DistributionCosts, OperationCosts, MaintenanceCosts, EndOfLifeCosts, StoringCosts, RiskCosts, MaintTaskCosts
Condition	Asset health condition, health prediction, sensing, measurements and inspections.	Site, Meas_device, Measurement, Unit, Asset, Segment, Alarm_region, Alarm_type, Event, Recommendation, Agent
Reliability	Historic data of completed maintenance tasks, design reliability data, and failures	Asset, Segment, Model, Function, Function_event, Function_recommendation, Event, Event_type, Measurement, Agent, Recomendation

The usage of this data model enables several functionalities, compared to a usual CMMS:

- Efficient management of configuration, without duplicities.
- Traceability of changes performed in the asset.
- Asset changing the asset which belongs to (e.g. dismantling).
- Asset location, that is, current site where the asset is located.
- Configuration linked to work orders.
- Asset costs during their life cycle.
- Costs at Maintenance operation level.
- Set up of parameters defining the preventive period.
- Configuration management along with reliability information, taking into account the record of changes performed.

5. CONCLUSIONS

Taking into account the basic functions of the configuration management (identification, control, status and audit), the research was focused on the identification phase with a big effort in the standard review.

There are different standards which solved configuration management issues, but it is important to prioritize the usefulness of these guidelines for maintenance and logistics of the transport sector. Configuration standards were reviewed and classified.

It is essential to have a good definition of the data model, with several information layers for configuration management, thus it is possible to work in a scalable and coordinated manner. 9 information layers were defined dealing with “Assets” as the central core of the information. Information layers are related to operation and maintenance planning, as well as to cost analysis.

A real configuration and maintenance management use case was employed to establish deficiencies and then evaluate the applicability of our data model based in the standards. In general terms there are too many classes in all layers. Conceptually the data model is correct, but class excess requires a complex and expensive conservation of information management.

The definition of this data model will enable a more effective maintenance through a better traceability of equipment, also improving maintenance logistics, knowing the actual configuration of an asset, or enabling comparisons between several machines configuration.

Next steps will be continuing working in the conceptual data model, in addition to the physic aspect of the data acquisition in line with the model.

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8.11 Optimizing E-Maintenance Through Intelligent Data Processing Systems.

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Resumen

El mantenimiento y la gestión de activos se ha ido remodelando a medida que han aparecido nuevas tecnologías clave que están teniendo un impacto significativo en las aplicaciones diarias. La creciente maduración del mantenimiento semántico y basado en la web, la ubicuidad de la computación móvil y los menores costes y el aumento de las capacidades de las tecnologías de detección e identificación, se encuentran entre las tecnologías habilitadoras que tienen el impacto más significativo. Este artículo analiza estas tecnologías claves, junto con sus perspectivas de adopción y los obstáculos que impiden una mayor penetración del E-mantenimiento en la industria.

OPTIMIZING E-MAINTENANCE THROUGH INTELLIGENT DATA PROCESSING SYSTEMS

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The landscape of maintenance and asset management has been reshaped as key technology enablers are making a significant impact on every day applications. The growing maturing of web-based and semantic maintenance, the ubiquity of mobile and situated computing and the lowered costs and increased capabilities of wireless sensing and identification technologies are among the enabling technologies having the most significant impact. They are recognised as the key constituents of e-Maintenance, the technological framework that empowers organisations to streamline their asset management services and data delivery across the maintenance operations chain. This paper takes a look at these key contributing technologies, alongside their adoption prospects and current hurdles preventing the wider penetration of e-Maintenance in industry.

1. INTRODUCTION

During recent years, e-maintenance has become more and more popular. The rapid penetration of web-based, mobile and wireless technologies in enterprise operations, alongside shrinking costs and increasing capacity of hardware, is changing the landscape of maintenance practice. At the same time the manufacturers of machinery are strategically moving towards developing service business for taking care of their products throughout the entire life cycle of the equipment [1, 2]. In order to be able to do this the manufacturers need tools for taking care of the machinery in a profitable and reliable way and this is where e-maintenance comes to the picture. E-maintenance can be considered a technology where information is provided where it is needed and maintenance is a task that is about information when done in an effective way. In modern maintenance scenarios the actions are carried out at optimal timing before breakage and are based on need not on calendar. In recent years quite a lot of research has taken place covering various aspects of e-maintenance. The EU FP6 funded Dynamite project (Dynamic Decisions in Maintenance, IP017498) developed and tested a set of methodologies and tools to support the e-maintenance processes. The results of Dynamite are summarized in the recently published book on E-Maintenance [2]. The technological developments included smart tags, sensors, signal analysis, smart decision support, portable computing devices, maintenance web-services, common database schemas, diagnosis, prognosis, as well as financial cost-efficiency assessment. It has been argued that such technological advancements are likely to provide a boost to modern industries in their pursuit of upgrading their overall efficiency in managing their assets [3, 4].

This paper tries to take this issue a little further and thus in the following paragraphs the future development of some of the key areas of e-maintenance are discussed and such aspects as identification technologies, wireless sensors, mobile devices, Internet, distributed computing, use of Internet and data, and diagnosis & prognosis technologies.

2. WIRELESS SENSING AND IDENTIFICATION

Industry employs condition monitoring systems which are now rapidly adopt technology innovations. The most significant upgrades in the technical infrastructure of condition monitoring systems are related to their increased computational capacity and the increased versatility offered by the incorporation of different wireless protocols, as advanced mini and micro-scale components and RF are integrated within sensor boards. This empowers the sensing end of the condition monitoring system to offer increased computational and connectivity support, making it easier to integrate supporting logic and tools, such as novelty detection, diagnostics & prognostics, as well as enhancements in computerised maintenance management systems and remote services.

Wireless sensor networks offer easy and customizable deployment of several sophisticated agents of small form-factor, making them suitable for wireless condition monitoring with sensor-embedded intelligence [5, 6]. These monitoring units can act as agents, capable of hosting automated computational and data storing operations that scale from filtering and pre-processing, to novelty detection and diagnostics. This has brought about a growing wave of in the manufacturing area, wherein more scalable installations of wireless condition monitoring systems begin to co-exist alongside their wired counterparts [7]. Based on wireless condition monitoring components and systems, maintenance service providers are now not limited to employing static monitoring infrastructures and solutions. Condition monitoring data and services can now become ubiquitously available to technical staff, via mobile and handheld devices, or remotely via the web, coupling to services residing directly in the sensing infrastructure. Increasingly, wireless condition monitoring is making headways to industrial practice, primarily in the area of (SHM) [8] and equipment or process monitoring [9].

The flexibility offered by wireless condition monitoring allows a multitude of customisable readings to be taking from measurement points, while simultaneously executing data-processing routines and algorithms at the sensor node level, or collectively, by a cluster of sensing nodes. The capacity to host such data-processing services at the sensor node or the wireless sensor network level has a direct impact on the nature of the monitored asset itself, embedding an increasing level of self-aware operation [10].

Alongside wireless sensing, asset identification is enabled by the usage of auto-identification technology, such as RFID and image tags. RFID usage upgrades the asset capability to store limited information locally, facilitating on-site information data storage and retrieval. Among the initial beneficiaries of RFID adoption was supply chain management [11]. With increased interoperability offered and strengthened by the adoption of electronic product control (EPC) standards, RFIDs have emerged as a natural link between the physical and the IT world, supporting the concept of the self-serving asset[12]. Integrating asset identification with wireless sensing offers a strong drive to contextualise maintenance data and services delivery, e.g. sensor readings are linked to a specific asset, which in turn operates under certain conditions and work load [13].

An emerging trend is related to merging sensing with asset identification, such as in Intel's WISP platform [14], a feature particularly relevant to e-maintenance. Furthermore, WISP supports energy efficiency, by adopting self-powering technologies, typically energy harvesting. A further push for the wider applicability of asset identification technology may be offered by tag-printing technology, similar to that of inkjet printing [15], while the potential to integrate in the same production process both sensors as well as RFID tags is promising. If the technology push is successful and commercially viable, enterprises will be able to produce their own tags to adapt to their ever changing asset management needs, with only limited additional resources and no re-integration costs.

3. MOBILE DEVICES AND DISTRIBUTED COMPUTING

With the increasing usage of wireless technologies and smart phones, data related to CM and equipment maintenance can become ubiquitously available to personnel, through handheld devices, or on the internet by simply linking to relevant maintenance services, provided by remote servers or by the asset monitoring facilities. This new perspective has created a potential new market niche [16]. In fact, Cloud Computing is emerged as a commercial reality, related to both the applications delivered as services over the Internet and the hardware and systems software in the datacenters that provide those services [17].

Maintenance service providers can offer highly efficient and customizable software solutions. Increased interconnection allows seamless operation, exchanging data between middle and upper level software, such as CMMS or ERP, and various wireless sensing and input modules. This is the essence of what has been referred to as Mobile Maintenance Management [18]. In this sense, it is possible to use handheld devices, such as PDAs, as well as miniaturized sensor solutions within a more flexible and decentralized CM and maintenance management integrated environment [4, 19]. This environment involves the use of mobile devices to perform typical maintenance management tasks such as work order management, communication with the service centre, asset maintenance tactical planning, reporting work, availability and location, retrieving maintenance history or documentation etc. Although most of these services are offered by existing systems such as ERP or CMMS, the industrial user would much rather work with a simple device offering a limited but clear set of interaction interfaces to retrieve or entry maintenance data. Thus, the user is empowered to become a dynamic mobile actor, operating in a dynamic environment, carrying the capacity to perform maintenance tasks with the support of ubiquitously available maintenance-supporting IT tools [20, 21]

With maintenance personnel becoming involved as mobile actors in the asset management process, it has also become important to seek to tailor the offered services to the exact needs of each actor. These needs depend on the role and function of the personnel, but also on the specific circumstances of the maintenance service request. For example, upon receiving a specific maintenance task order, industrial staff would need to locate the asset on the shop floor, have access to its maintenance history, retrieve information about spare parts availability, or indeed perform a condition assessment audit with the help of the PDA and sensing modules. Tailoring the available services and information availability to the specific demands is a feature that has been sought at a premium and is often referred to as context-aware or situated computing. The notion of context has been linked with computing for many years, largely associated with computational linguistics. Since the mid 90's, there has been increasing attention to the role that context might have in adaptive computing. Specifically, the interest focused on how computer applications can be adapted to match the requirements or needs of different situations and users. With the prevalence of service-oriented computing, adaptation capacity has become synonymous to adapting the offered services and content. Consequently a context-aware maintenance support system is expected to tailor each service to the apparent usage context. This is often perceived by users as a capacity to provide 'intelligent content' or 'intelligent services', often presented through 'intelligent interfaces'. Yet it is only following the deeper penetration of mobile and wireless technology into maintenance and engineering asset management practice that contextualized computing emerges as a significant element in modern and future maintenance management practice.

The use of augmented and virtual reality is also posing significant issues related to context, as the perceived experience in such applications critically depend on the successful user immersion in a contextually relevant situation. The mobile maintenance actor may employ different devices for different services, at different locations and at different times. The actors are using the mobile devices in different maintenance task contexts. A typical example is a mobile actor employing a PDA in relation to a CM task. The PDA can be employed in tandem with an identification scheme, such as a localization technique or radio frequency ID (RFID) tag, to identify the monitored asset and obtain a better understanding of the task in hand. The PDA can be employed to support diagnosis and prognosis. This implies higher demands in data availability and CPU power, not yet readily available in industrial PDAs. Part of the processing can be undertaken by smart sensor solutions, delegating some of the CM tasks to the lowest possible processing level, the machine level. The developed solution must strike the right balance between local processing and information exchange between devices, implying trade-offs between energy efficiency, processing capacity and the quality of the maintenance decision support process. In the future, additional support may become available through more extensive use of virtual and augmented reality solutions, which can help to 'immerse' the mobile actor in almost-real life scenarios and 3D machinery models, providing more practical on-site. However, these solutions are still in their infancy and not widely available in current industry.

4. INTERNET AND DATA

The internet is considered as a disruptive technology because of its impact in the world and business, enabling a distributed communication and data storage, in synergy with other communication technologies. For maintenance purposes the internet has been crucial in the maintenance concept, along with web services, which are becoming a fundamental technology for performing e-maintenance. Web services allow the central processes in e-maintenance through the existence of distributed services to perform information analysis, management, order execution, even data capture. Computers attached to the internet are able to interchange messages through web services, since the HTTP port used by web services is always open, even in the most restrictive firewall configurations. Furthermore, the semantic web is a world-wide project which intends to create a universal medium for information exchange by giving meaning (semantics) to the content of documents on the web, so that they are understandable by machines. The semantic web provides the required data in real time, supported by web services, in a future e-maintenance scenario [22, 23]. Nevertheless, the adoption of this new architecture is a slow process for different reasons. Usually companies have a lot of information in paper format, and it is not always easy to make changes in the company culture. Also the adoption of a standard for data format is required, that would support products through their life cycle and the integration of different technologies. The communication among distributed components needs a protocol, but the complexity makes the management of data a key issue, that should be managed in a centralised way.

The MIMOSA organisation has been dedicated to developing and encouraging the adoption of open information standards for Operations and Maintenance in manufacturing, fleet, and facility environments for some decades. MIMOSA provides the standard OSA-CBM (Open Systems Architecture for Condition Based Maintenance), for information acquisition processes, developed to support interoperability through different CBM components. The standard OSA-EAI (Open Systems Architecture for Enterprise Application Integration), also provided by MIMOSA and complementary to OSA-CBM, was created to solve the problem of integrating different applications. OSA-EAI is essentially a large database composed of hundreds of tables. The MIMOSA definition covers different issues related to measurements, condition monitoring, diagnosis, prognosis and management of maintenance work orders. However, the main drawback is the adoption of OSA-EAI in companies, which may be a difficult step if relational data-bases are not familiar. OSA-EAI is well documented and is quite easy to download and install, but it is not an easy step to start using a database in a logical way. Actually the installation requires higher level effort in discussing how OSA-EAI should be used in order it to be an effective tool. But one must ask if this is a hopeless route, since it is necessary to understand 100,000 items in a standard simply for definition of concepts. Another problem is to keep the database up to date. The semantic data ultimately has a low level definition, which offers many degrees of freedom. In order to provide interoperability among components and software, more effort is needed to provide a useful and easy way to interchange data. Another very important set of standards is not related to specific task modelling, but instead to facilitate data integration among different tasks.

5. DIAGNOSIS AND PROGNOSIS

The multi-signal analysis and management is a challenge, that is, how to manage the data so that it is available for analysis and data from several sources can be integrated and also saved for later use for supporting the diagnosis and prognosis task. Usually data is stored in hardware specific format even though MIMOSA aims for a common definition of data format, since several hardware solutions can support different analysis tools.

The transformation of maintenance strategy, and the escalation in the number of sensors and condition monitoring, will lead to pronounced need for automatic diagnosis, which also means that a massive leap forward has to be taken. The status of automatic diagnosis is still low in industry. For example, few consistent solutions are used in condition monitoring of rotating machinery, even though a lot of research has taken place in this field. It would seem that in many cases the researchers have not had a wide enough view of the problem they have tried to solve. There are several studies about classification using e.g. neural networks and consequently a great number of solutions have been developed which work in the laboratory with the type of data they have been trained with, but not in the field (see e.g. [24]). It would certainly seem that many researchers are naive if they assume that an ingenious classifier can solve the problem outright. The right kind of sensing of a physical phenomenon, and appropriate signal analysis, are essential – poor quality data will offer little chance of reliable classification. Many corporations are moving towards the provision of services for the machinery they produce, and much data will become accessible to support the condition monitoring task. Improved understanding of wear models for machines will especially help in the computerisation of diagnosis. It is predictable that more process data will be accessible; simulations will be available and they make available supplementary information to support diagnosis and prognosis. When the improvement of signal analysis techniques is taken into account, the automatic diagnosis of the condition of machinery components can be anticipated to take a big step forward, and become more available for many kinds of components.

Additionally the prognosis of failure development of components suffering from wear as a function of loading will become possible on a level that supports the introduction of CBM. Due to the difficulty of diagnosis and prognosis of rotating machinery, data mining and classification techniques as such do not really give a lot of support, but they will be very beneficial in handling spare parts, and reserving resources, based on more statistical than physical modelling. The ordering of spare parts and their administration will become semi-automatic. It is natural to start from the less costly parts that are used in numbers and then in time go to the more expensive and rare parts, where a human inspection process will probably be used for quite a long time in the future. Modern e-maintenance solutions could already carry out all the ordering and work force supervision automatically, but the potential for errors, e.g. sending out the wrong orders for parts and works is restricting this development. However, this process will naturally go further as more experience is gained from semi-automatic solutions.

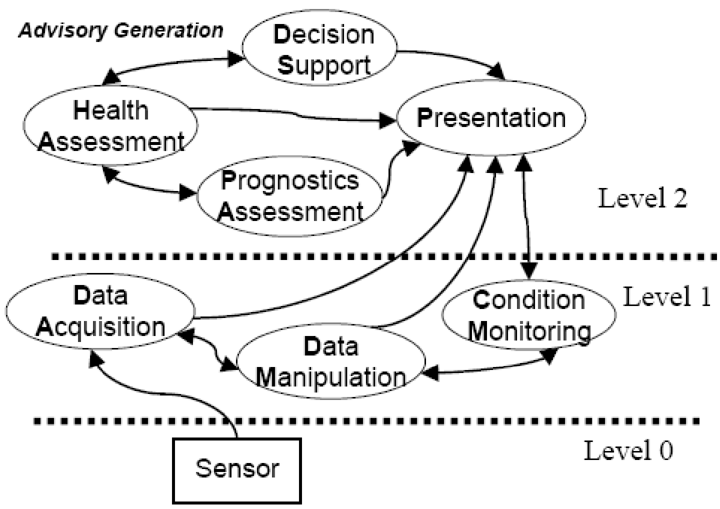

Figure 1. Correlation between OSA-CBM and ISO activity level (ISO 13374)

6. CONCLUSIONS

During the last decade we have seen the progress of e-maintenance techniques. The key elements are the widespread use of Internet and quick progress of sensors and processing power. The use of e-maintenance at the moment still is at low level compared to the enormous potential but particularly inspired by the modifications of strategy of manufacturing industries towards the competence of providing services throughout the life time of the equipment they have manufactured will present a great increase in this technology. This step forward will be reinforced and supported by the hardware development but the most vital factor is the obtainability and usability of new data that can support diagnosis and prognosis and aid to raise them to a level that is of real assistance for the maintenance technicians. The advance of new signal analysis techniques joint with simulation models can be the aspect that truly means a breakthrough in prognosis of the life time of components of machinery and consequently real proactive CBM will be empowered. Many of the technologies are offered already now and their introduction could be straightforwardly vindicated economically but obviously it will take some time prior all the offered opportunities will be taken into use but naturally the accomplishment stories of those in the forefront will boost the adaption of new technologies in greater numbers.

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8.12 A multi-stage optimization algorithm for standardization of maintenance plans

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Resumen

La definición de planes de mantenimiento preventivo no es un problema fácil de resolver, especialmente cuando se trabaja con un parque de activos muy diverso. En estos casos se requiere de un proceso de estandarización que no es fácil de realizar, ya que conlleva incluir tareas no estrictamente necesarias de realizar en algunos activos. Este artículo presenta un algoritmo para resolver este problema de optimización combinatoria, utilizando un enfoque de múltiples etapas con 4 algoritmos diferentes.

A multi-stage optimization algorithm for standardization of maintenance plans

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Abstract: The main objective of maintenance is to increase equipment lifetime while keeping the efficiency and reliability of the systems in operation. However, the definition of the preventive maintenance tasks is not an easy problem to solve, since in many cases tasks performed on assets can be redundant, not required and it is then difficult to define cost-effective maintenance plans. Therefore, a more accurate definition of plans is needed to reduce maintenance costs, where different optimization algorithms can be used. Taking a single one-stage approach could serve to find an optimal solution depending of the use case, but a unique algorithm does not find reliable results in a generic way. This paper presents an algorithm to solve this combinatorial optimization problem, using a multi-stage approach with 4 different algorithms. The experimentation shows that this novel approach obtains better results than the use of the individual optimization algorithms.

Keywords: Preventive maintenance, optimization algorithms, planning

1. INTRODUCTION

Maintenance research and development is gaining importance worldwide because of the irruption of technologies that enable advanced maintenance solutions (e.g. predictive maintenance). Another factor is the increasing relevance of maintenance activities as a factor to enlarge product life-cycle and to reduce wastes and energy expenditures due to recovery and manufacturing activities (Takata et al 2004)

Maintenance management involves different concepts and activities **(**Garg & Deshmukh 2006): Part of the literature deals with (a) development and selection of optimum maintenance strategies (Bevilacqua 2000) (Christer 1999) (Gilabert 2015) (Koren 2002) (Scarf 1997); other major areas of research describe (b) the modelling and programming of the machine maintenance (Duffuaa 1999) and (c) the theory of reliability, replacement and the determination of frequency of inspection (Jardine 2001). Finally, other researchers concentrate on (d) simulations to measure a maintenance system (Banks 2005) (Barros 2003).

In this paper our objective is to focus on a problem related to maintenance strategies that is scarcely tackled so far in literature: It is related to the development of standardized maintenance plans related to PM tasks, in complex maintenance scenarios with different fleet characteristics as well as maintenance resources. These scenarios appear in areas such as fleet transport systems (buses, trains), infrastructures, or elevators. Here, Preventive Maintenance (PM) tasks should be identified and developed to manage the failure. PMs are value-added tasks conducted using the least labour, downtime and materials to complete the tasks. Therefore, fleet maintenance requires standardized job plans. And the definition of plans concerning the PM tasks to be done by maintenance crew is a crucial problem prior to resource planning.

The development of these plans is not trivial. Product maintenance specifications can include up to one hundred different actions, to be executed with different frequencies, and with some differences depending of product versions. On the other hand, not all maintenance crew is able to execute all actions (some of them may be better reserved to senior specialists) and there may be even different contracts regarding the frequency of inspections depending on the SLA (service level of agreement contracted) or the country legislation, to name only some examples.

These characteristics fits as a challenge for automated decision-making trough expert optimization models. Decision making tools help users to improve the ability of solving problems and the capabilities of production systems (Hastak 1994) (Medina-Oliva 2015) (Molenaar 2001). Techniques and applications used are very diverse, such as artificial intelligence and expert systems, database queries, or genetic algorithms (McIntyre 1998) (Ripen 2005). The traditional definition of decision making systems is as follows: a computer or computer environment to assist people in making decisions (Molenaar 2001). These systems do not usually give a direct solution of the problem but help the user to add value to the system output when deciding.

Optimization is also linked to decision-making, minimizing the maintenance costs or the ecological impact (Jiang et al 2018). In this case, the standardization of maintenance plans cannot be solved usually by accurate optimization algorithms, which are those that guarantee finding an optimal solution. What disables the application of accurate optimization algorithms to these problems is the computation time. This fact has a consequence in the scientific community: it is the born of meta-heuristics techniques. Despite not finding the optimal solution, these techniques ensure that there is a good solution with the advantage that this search could be carried out in a reasonable execution time. Therefore, depending on the needs, there can be multiple optimization criteria simultaneously. It is possible to have different optimization systems or include commitments for calculations with partially connected criteria.

2. THE PROBLEM OF MAINTENANCE PLANS

Usually the maintenance companies define maintenance plans as a set of multiple tasks of short duration. For instance, in case of a car could be (a) check tire pressure, (b) change oil and filters and several other tasks with a pre-defined duration and frequency. The definition and realization of these tasks depend directly on the configuration of the assets, while the corresponding legislations must be applied. Therefore, theoretically it would be best to define a different maintenance plan for each specific asset. Reality tells us that this is unfeasible, since the operators in charge of carrying out maintenance tasks cannot have a specific plan for each asset they work on, being more efficient to define a single plan (or a reduced set of plans) so that the operator performs them efficiently.

For this reason, maintenance plans must be standardized for all assets in a system, even if this implies the execution of tasks that are not strictly necessary on certain assets. Some maintenance factors or policies have an influence and must be considered when making the definition of the plans. These considerations suppose a problem of combinatorial optimization. The optimization problem must take into account the following factors, considering that it applies to a set of assets of a similar nature:

- Each asset has a set of tasks to execute depending on its configuration.

- Each task has a minimum frequency of realization, defined in times/year. This frequency depends on different legislations, safety criteria or customer requests.

- The asset belongs to a client, that depending on the contract can have certain additional tasks (e.g. cleaning) or tasks that are made more frequently.

- The tasks to be executed on an asset are grouped in different plans, due to their different frequency requirements.

- The maintenance of an asset requires N plans carried out in V visits and by a certain operator skill. Obtaining the number of visits associated with each plan is another optimization problem.

- Some tasks can be done by several operator profiles: its own required profile or an upper one.

- It should be possible to establish a maximum plan duration.

- A balance parameter can be set, defined as the maximum difference of minutes between plans. The maintenance company is not interested in having very unbalanced plans, because a later planning of the fleet will be much more complex.

The optimization methods addressed to tackle this problem that appears in literature are varied: Some of the optimization criteria are related to smoothing the preventive maintenance work load of the crew (Ben-Daya 2009), other related to short-term (Dedopoulos 1995) and long term (Garg 2006) scheduling of planned maintenance work. Multi-stage optimization has been also used in maintenance for determining periodic inspections (Phan & Zhu 2015). Instead, this paper is centred in optimizing the group of tasks to be done by the maintenance crew in a fleet, taking into account that having too much different task plans could be difficult to be managed by the staff.

3. THE PROPOSED ALGORITHM

The algorithm defined to solve the proposed problem, consists of solving 2 optimization problems:

P1: Input data only provides the total number of plans and visits related to the asset, so it is needed to find the best combination between plans and visits. For instance, the requirements could be 2 plans in 6 visits, and the algorithm must give as a result that Plan 1 should be done in 2 visits and Plan 2 in 4 visits (or maybe other combination as 1-5 or 3-3).

P2: To find the best standardization of tasks in the plans/visits to perform, according to the input requirements.

Figure 1 depicts the algorithm architecture used in the multi-stage optimization.

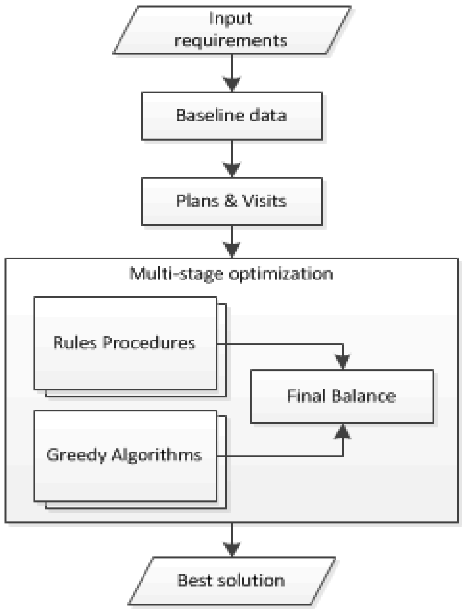

Fig. 1. Multi-stage optimization algorithm architecture.

In the following subsections each step of the algorithm is briefly explained.

3.1 Input Requirements

During the first step the input information must be provided to perform the optimization. In detail:

- Main asset configuration. The concept of a plan standardization is not to provide the specific configuration, but it should be defined in an upper level (e.g. in case of cars, they could be gas or diesel, involving different maintenance tasks).
- Country legislation.
- Client contract type.
- Operator profiles. For instance, Basic and Expert.
- For each operator profile, number of plans and total visits.
- Maximum duration of plan in minutes.
- Maximum difference among plan durations in minutes (B).

3.2 Baseline data

According to the previous input requirement, the baseline data is obtained. This data consists on a set of tasks and their compulsory visits for each task. The Optimal Time is defined as the sum of these task durations multiplied by their visits. This Optimal Time will be used for validation purposes.

$$OT = \sum_{i=1}^{i=m} t_i \, v_i$$

where *m* is the total number of tasks, t_i is the duration of the task and v_i the minimum number of visits of t_i.

3.3 Plans & Visits

As introduced before, obtaining the number of visits associated with each plan is another optimization problem. The maintenance of an asset requires N plans carried out in V visits and by a certain operator skill. This is calculated by another instance of the multi-stage optimization algorithm, detailed in the next point. However, this execution is performed in a small number of iterations (< 10).

The target of this step consists in selecting the most appropriate plans/visits relation so that the search is more limited, and the search algorithm starts from a defined configuration. The step in this process starts with the calculation of all possible combinations of visits and plans by operator profiles. For example, for an expert profile, 3 plans and 6 visits (Expert-3-6), the number of visits of each plan could be: 1-1-4; 1-2-3; 2-2-2. For each possible combination, the multi-stage algorithm with 10 iterations is executed. The best result obtained (E.g. 1-2-3), is the configuration used in the next step.

3.4 Multi-stage Optimization

In this step, the tasks are distributed in the maintenance plans, which have previously been assigned a certain number of visits. This process is done in 4 different algorithms, obtaining as a result the best plan provided after the execution of: (1) Rules procedure minimizing time, (2) Rules procedure balancing plans, (3) Greedy algorithm minimizing time, (4) Greedy algorithm balancing plans. The evaluation criterion is defined as the difference between the Total Time and the Optimal Time calculated in the previous step. At the same time, 2 different objectives are managed*:*

- The minimization of the total time required to perform the plan on the asset, that is, the sum of all tasks in visits, in every plan.

$$min \sum_{i=1}^{i=n} \sum_{j=1}^{j=m} t_j v_i$$

where *n* is the number of plans, *m* the number of tasks related to plan *i*, t_j the duration of task *j*, and *v* the number of visits of plan *i*.

- The minimization among the differences in duration of plans (maximum balance)

$$\min\left(\left(\max_i \sum_{j=1}^{j=m} t_j v_i\right) - \left(\min_i \sum_{j=1}^{j=m} t_j v_i\right)\right)$$

3.4.1 Rules Procedures

This first procedure follows this sequence:

- Tasks are ordered from largest to smallest duration.
- Sequentially, each task is assigned to a plan, using this algorithm:
    - Selection of possible candidate plans: do not include the task previously and meet the operator profile requirement.
    - Select the plan where the number of times matches the number of visits of the task, or in its absence the smallest absolute difference.
    - In case of a tie, the plan with the minor number of visits is selected.

The second procedure follows a similar sequence, except in case of tie in last step: the plan with the minor duration is selected in this case. This change produces a more balanced result.

3.4.2 Greedy algorithms

The greedy algorithms are based on covering the complete space of possible solutions to the problem. We have selected the backtracking algorithm. This technique is the direct application of the search method known as first in depth. The algorithm consists on: (1) Select an option among the possible ones. (2) For each selection, consider every possible option recursively, in a loop (search in depth). (3) Return the best solution found of all evaluated solutions.

In our case, the first greedy algorithm performs this sequence: (1) If a task can be carried out by several profiles, all the possibilities are considered. (2) Combinatorial search of assignment of all possible tasks to each visit is done. That is, a visit could be considered as an empty box where the different combination of tasks are inserted.

The second greedy algorithm is similar except it works with sorted visits: in each search iteration, the visits are sorted by their absolute difference between the number of visits of the task and the number of visits of plan, prioritizing a maximum balance among the plans

3.4.3 Final Balance

The Final Balance consists of 2 procedures which works with the found solution, trying to improve it. The final balance follows this sequence: (1) A greedy algorithm that tries to remove the tasks of the plans that exceed the maximum allowed or the longest in case of not having it. It moves them to the plans of shorter duration. (2) If the flattening criterion (B) is not yet met, another greedy algorithm adds unrealized tasks to the plans of shorted duration. This Final Balance is applied in the execution of the 4 algorithms implemented.

4. EXPERIMENTATION

For validation purposes the experimentation has been conducted using truck forklift fleet job standardization. There are two types of forklifts in the fleet: electrical and diesel. Maintenance crew is divided into expert and basic technicians. The execution of greedy algorithms has been limited to 1000 iterations, and the execution time is less than 2 minutes. A short execution time is required.

The first experiment (1x) considers a region where there is a lot of diversity in maintenance plans. Therefore, the maintenance company needs to standardize the plans to solve the problem of diversity. In this case 6 visits are executed annually by one expert technician. The optimization has been performed setting 3 plans at 5 minutes of maximum difference in duration (*B*=5). The Optimal Time (OT) is 82.57 m. Table 1 provides results when the greedy algorithm is isolated from previous rules procedures.

Table 1. Greedy algorithm isolated in 1x

Skill	Plan	Visits	Duration(m)
Expert	#1	1	19.28
Expert	#2	2	16.92
Expert	#3	3	15.15

Annual total time: 98.57 m.
Difference OT: + 16 m.

However, when using the multi-stage algorithm, the annual total time for maintenance is almost 2 minutes shorter.

Table 2. Multi-stage algorithm result in 1E

Skill	Plan	Visits	Duration(m)
Expert	#1	1	19.21
Expert	#2	2	17.93
Expert	#3	3	14.21

Annual total time: 97.7 m.
Difference OT: + 14.13 m.

The usage of this multi-stage algorithm improves the results comparing the usage of just a greedy algorithm, and even the computational time is improved. Actually, the standardization of plans using the final result in Table 2, supposes an increase of 7% in annual total time maintenance, and therefore a similar increase in maintenance costs, but the company consider this as an indirect cost required that allows to save money in learning, reduce human mistakes caused by having too much different plans and simplify maintenance planning for maintenance crew load balancing.

The second experiment (2x) starts from a situation where an expert technician executes all tasks in 2 plans during 12 visits. In an annual maintenance, the first plan is executed every 6 months and the second one the rest of months. OT is 261.88 minutes. The initial results are shown in Table 3.

Table 3. (2x) Expert-2-12

Skill	Plan	Visits	Duration(m)
Expert	#1	10	18.65
Expert	#2	2	42.7

Annual total time: 271.91 m.
Difference OT: + 10.03 m.

The target is to save money using two technician profiles (expert and basic). In this case the expert technician executes 2 plans in 2 visits, and the basic one executes 1 plan in 10 visits. Table 4 shows how the expert skill improves the time while keeping the basic tasks duration, related to previous situation in Table 3.

Table 4. (2x) Expert-2-12; Basic-1-10

Skill	Plan	Visits	Duration(m)
Expert	#1	1	42.7
Expert	#2	1	32.68
Basic	#3	10	18.65

Annual total time: 261.88 m.
Difference OT: 0 m.

Even after setting a maximum difference among plan durations of 2 minutes by profile (*B*=2), the algorithm provides the results in Table 5.

Table 5. (2x) Expert-2-12; Basic-1-10; B=2

Skill	Plan	Visits	Duration(m)
Expert	#1	1	38.85
Expert	#2	1	38.53
Basic	#3	10	18.65

Annual total time: 261.88 m.
Difference OT: 0 m.

This result means an improvement of 10 minutes by truck. Assuming a truck fleet of 100 units and considering that basic technician cost/hour is 40% less than using the expert operator, the savings are close to 32% in this case.

5. CONCLUSIONS AND FUTURE WORK

This paper presents an algorithm to solve the combinatorial optimization problem in standardization of maintenance plans, using a multi-stage approach with 4 different algorithms. The usage of this algorithm allows to reduce costs or to enable an easier later planning. Taking one single algorithm could find an optimal solution depending of the used case, but a unique algorithm does not find reliable results in a generic way. This algorithm is completely scalable in number of tasks, plans, visits and operator profiles. However, after this work we considered that it is possible to take advantage of the combination of algorithms in other ways, that is, using a hierarchical approach. Next step will consider an Estimation of Distribution Algorithm (EDA) on the top, that will be fed by the optimal results found by 4 different kind of optimization algorithm: Rule-based, greedy, evolutionary and simulated annealing. Therefore, we go ahead in two ways, extending both the algorithms typologies and the way to combine them.

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8.13 A dynamic optimization methodology for maintenance and logistics

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Resumen

Al planificar el mantenimiento, es necesario tener en cuenta un conjunto de factores como el riesgo del equipo y la logística de las piezas de repuesto. El objetivo ha sido definir una nueva metodología de análisis de riesgo en línea que tenga en cuenta los factores dinámicos para su cálculo, para que luego pueda emplearse en las actividades de mantenimiento que se llevarán a cabo en aerogeneradores. Además, la integración de la perspectiva de logística y mantenimiento motiva la necesidad de organizar un marco de toma de decisiones que presentamos en 6 pasos secuenciales. En general, las estrategias de mantenimiento y reemplazo se tratan de forma separada o secuencial en la industria. Sin embargo, dado que el nivel de stock de las piezas de repuesto a menudo depende de las estrategias de mantenimiento, es mejor tratar estos problemas simultáneamente. En este artículo proponemos un algoritmo genético para resolver este problema.

A dynamic optimization methodology for maintenance and logistics

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Abstract
The main objective of maintenance is to increase equipment life while keeping the safety and reliability of the system. When planning maintenance, it is necessary to take into account a set of factors such as the risk of equipment and the logistics of spare parts. The objective has been to define a new on-line risk analysis methodology that considers the dynamic factors for its calculation, so that it can later be used in the maintenance activities to be carried out in the wind turbines. In addition, the integration of the logistics and maintenance perspective motivates the need to organize a decision-making framework that we present in 6 sequential steps. In general, maintenance and replacement policies are treated separately or sequentially in the industry. However, since the stock level of spare parts often depends on maintenance policies, it is best to treat these problems simultaneously. In this article we propose a genetic algorithm to solve this problem.

Keywords:
Risk management, Maintenance, Logistics, Genetic Algorithms

1 RISK BASED MAINTENANCE

The risk calculation, for operation and safety, is usually a static calculation in the design phase. In the current context this is no longer sufficient, and the objective has been to define a new online risk analysis methodology that takes into account the dynamic factors for its calculation, so that it can subsequently be used in the maintenance activities to be carried out in wind turbines.

The main objective of the maintenance processes is to make use of the knowledge of failures and accidents to achieve the highest possible safety at the lowest cost. Also the challenge of the maintenance engineer is to implement a maintenance policy that maximizes the availability and efficiency of the equipment, controlling the deterioration, ensuring a safe operation for people and environmentally, as well as minimizing the total cost of the operation [1]. There is also a close relationship between maintenance and product quality, since the quality of the product depends on the condition of the equipment.

Therefore, it is necessary to carry out maintenance planning, minimizing the frequency and consequences of failures. The risk-based maintenance methodology (RBM) is designed to study all failure modes, determining the risk associated with each of them and developing a maintenance policy that minimizes the occurrence of high-risk failure modes. In this paper we propose our own risk calculation methodology based on RMB, that is dynamic over time, in order to prioritize maintenance actions based on the current risk.

In the literature review, different approaches based on risk-based methodologies have been carried out. Vesely [8] used probabilistic risk (PRA) as a tool for maintenance prioritization.

Vaurio [9] presented a procedure to optimize the intervals of testing and maintenance of systems and components related to safety. The method is based on minimizing the total cost of the plant under the restriction that the total frequency of accidents (risk) remains below an established criterion.

Backlund and Hannu [10] discussed maintenance decisions based on the results of the risk analysis. Effective use of resources can be achieved using risk-based maintenance decisions to determine where and when to perform maintenance. A comparative study was discussed based on three independent risk analyses performed at a specific hydroelectric plant.

The risk-centred approach used in these studies helps make decisions regarding the prioritization of equipment for maintenance and in determining an appropriate maintenance interval.

Risk-based maintenance (RBM) consists of 2 phases [2]:

1. Risk assessment.
2. Risk-based maintenance planning.

The main objective of this methodology is to reduce the general risk that may arise from unexpected failures in the facilities [3]. Inspection and maintenance activities are prioritized based on the quantified risk caused by the failure of the components, so that the total risk can be minimized using risk-based maintenance. High-risk components are inspected and maintained normally with greater frequency and thoroughness and are better maintained, in order to achieve tolerable risk criteria [4].

Risk assessment is the critical and most important phase, since maintenance decisions will be made with the risk assessed as a centre.

All risk analysis methodology must have an estimate of failure frequency, an estimate of the consequences and an estimate of the risk. In the case of the RBM strategy, it is necessary to better define an adequate maintenance policy. This can increase the reliability of the equipment and lead to safe and faultless operations. Although RBM is widely recognized as an important tool for accident analysis, it is not fully utilized. The RBM process is often used on a static basis considering only major incidents and accidents. Too often ignores minor incidents or near accidents. In addition, it has not been used in decision making dynamically.

The risk assessment can be quantitative or qualitative. The quantitative risk assessment is carried out by estimating the frequency and its consequences. Quantitative risk assessment is only appropriate when it is reasonable and feasible of calculate.

The qualitative risk assessment is applicable when the risks are small and well known, and the site is not in the neighbourhood of a possible incompatible development. A simple description of the types of serious faults, their consequences and their probability and a review of compliance with the standards are sufficient. The results are represented as a risk matrix where the probability and the consequences represent the axes.

When there is data available, the criticality number (CN for its acronym in English) is calculated as follows:

Criticality Number (Cm) = $\beta\alpha\lambda t$

where β = Probability of failure effect, α = failure mode ratio, λ = component failure rate, t = operating time

In the Failure Mode, Effects and Criticality Analysis (FMECA), CN is not used, but the Risk priority number (RPN) is used, defined as follows:

Risk priority Number = Severity x Occurrence x Detection

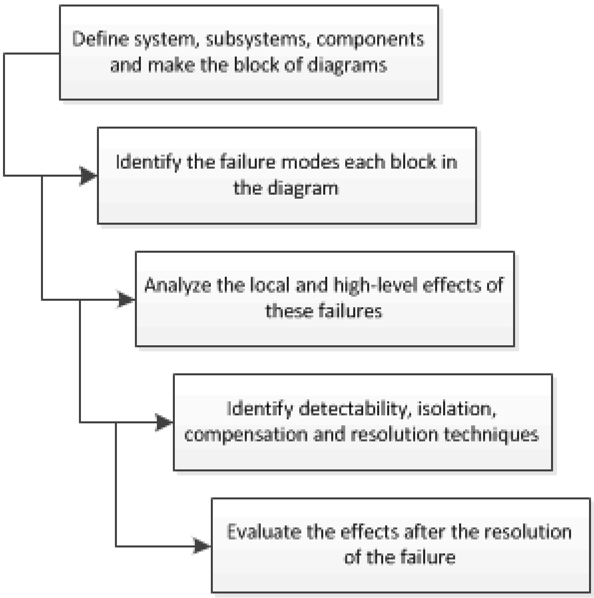

Figure 1: Steps for the design of an FMECA

The severity indicates the consequences of a failure, the occurrence indicates the probability of the failure to occur, and the detection is how easy to detect. In this way a ranking is made with the failures from higher to lower RPN. The range of RPN varies between 1 and 1000, as a value that indicates the need to perform maintenance.

Sinha [10] proposes a modification of the methodology for calculating the value of RPN in FMECA and applies it to an offshore wind farm. If there is no numerical information available, it proposes a qualitative approach.

2 METHODOLOGY FOR DYNAMIC RISK CALCULATION

Normally the risk is defined as the multiplication between the cost of the failure by its probability.

Risk = Failure Cost x Failure Probability

Depending on the application where the costs are calculated, a structure of different costs is usually used, although in the literature they usually categorize it into economic, environmental and security costs. The economic costs can be categorized in very complex ways, although fundamentally they are divided into repair, loss and penalty costs.

Figure 2: Cost categories that influence the risk

When we talk about a dynamic calculation of risk, we must bear in mind that values may vary when calculating the risk. Basically, we can specify 2 aspects:

1. The probability of failure can be dynamic over time. As the fault database increases, the probability of each failure mode evolves.
2. The impact according to current operation, that is, the economic cost of the loss. Depending on the current activity of the asset being considered, the losses are higher or lower.

In this work and most of the bibliography focuses mainly on the first point. For example, Bhandari [6] presents the Dynamic Risk-based Maintenance (DRBM) methodology that uses Bayesian theory to update the probability of the occurrence of events. This methodology can produce more consistent and accurate maintenance inspection intervals. It can also incorporate the conditional dependencies of the subcomponents that could be lost during the application of conventional methods. The evaluation of this dynamic risk is carried out in 2 stages: analysis of accidents and updating of the probability. A Bayesian network is used in these steps, updating the probability of failure, and then the risk. The probability is updated when new information is available.

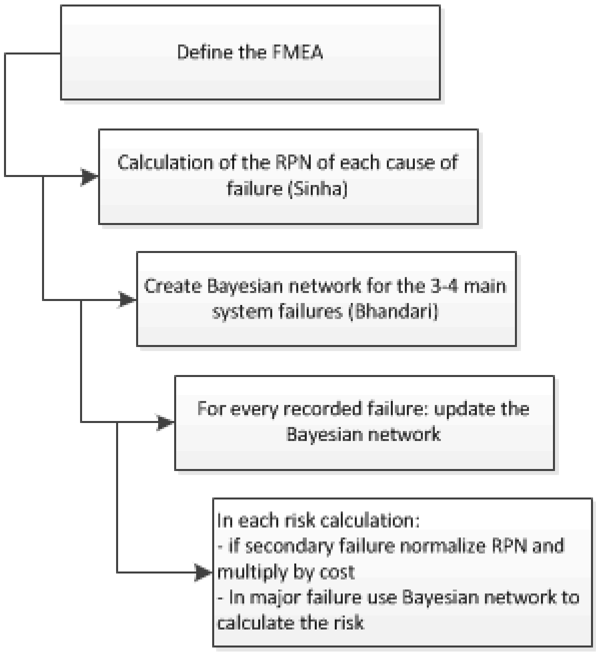

Figure 3: Methodology for dynamic risk calculation

In this paper we propose a method for the dynamic calculation of risk, which is reflected in Figure 3.

Next, we describe the different steps of the methodology:

1. Design the FMECA of our system, in the traditional way (Figure 1).
2. Calculate the value of Risk Priority Number (RPN) for each cause of failure, according to Sinha's

calculation method [7], which uses a method with a smaller range of values.

3. We select the main failures of our system (3 most critical failures).
4. We designed a Bayesian network for each selected primary fault.
5. When a high-risk failure in the system is present, the corresponding Bayesian network must be instantiated, with the causes detected in such a way that the adaptive method of the network is applied.
6. When calculating the risks of failure modes, we must:
    a. If it is a low risk failure, we must use the previously calculated static RPN value, normalize it and multiply it by the cost of the failure.
    b. If it is a high failure risk, we instantiate the Bayesian network to obtain the inferred risk (value between 0 and 1) and multiply it by the cost of the failure.

The learning of a graphic model has become a very active research topic and many algorithms have been developed for this. Introductory and advanced information on probabilistic network learning can be found in [5]. Here, we can distinguish between three approaches:

- Learn the structure: this type of learning tries to make the whole structure of Bayesian networks through a fusion of data and expert knowledge. Methods for structural learning include Naïve Bayes approaches, search and scoring methods (K2) and dependency analysis (PC, NPC).
- Learn batch probabilities: learn the information regarding conditional distributions. The parameter estimation uses algorithms such as EM (Estimation-Maximization) to find the best parameter distribution given an a-priori graph configuration. This approach and the previous one need a much larger case database.
- Learn the probabilities sequentially: this approach is used when we have a certain structure, but we want the probabilities to be adapted to a particular context. It is also called "adaptation".

In our case, we must structure the network in the way defined by Bhandari, and we can see in Figure 4.

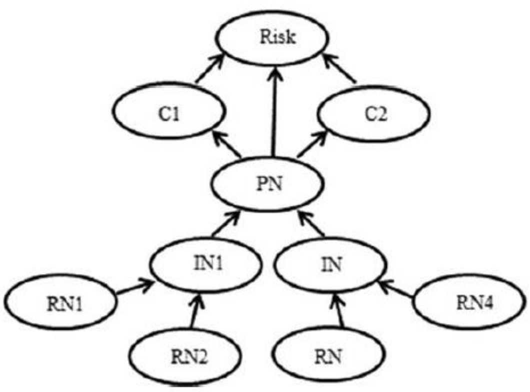

Figure 4: Network structure used by Bhandari [9]

This network is structured as follows:

- Root Nodes (RN).
- Intermediate nodes (IN)
- Top or pivot (PN) nodes, the failure mode that we are defining to obtain the risk.
- Consecutive nodes (C)
- Final risk (Risk), related to the consequence nodes and the pivot node.

The consequences can be estimated in 4 categories:

- Human damage.
- Economic losses.
- Environmental losses.
- Performance losses.

In this way, the risk calculation according to the category can be prioritized. The pivot node is connected to each consequence. This node calculates the final risk from the failures of individual components. In the next step, the risk level is estimated with the Bayesian network considering the probabilities of failure and the relevant consequences. The calculated risk level reflects the level of risk in the system. The risk can be categorized as low, medium and high.

3 LOGISTICS AND SPARE PARTS MANAGEMENT

The integration of the logistics and maintenance perspective motivates the need to organize the proposed decision-making framework in 6 sequential steps. These specific problems are evidence of the main questions that generally arise during the decision-making process to define the correct management policy for spare parts.

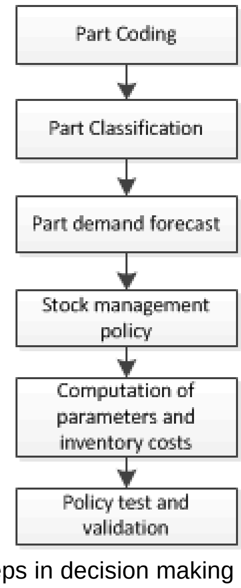

Figure 5: The steps in decision making for selecting spare part policy

3.1 Part coding

A specific code system will be used for spare parts, which is quite different from that adopted in a list of product materials; the code should provide a quick understanding of the technical characteristics of the item, the equipment tree it refers to, the supplier involved and the physical location in the inventory .

3.2 Part Classification

An adequate classification of the spare parts is needed because in a production plant, composed of different equipment, there is a great variety of technical spare parts used directly or indirectly for maintenance and repair purposes. In addition, its intrinsic technical and economic characteristics (criticality, specificity, value, type of suppliers, etc.) can be very different. As a result, an adequate classification system must provide fundamental information to establish the correct repair policy. For the classification of the parties and for the prioritization a classic methodology to carry out the process is usually called the ABC Classification.

3.3 Part demand forecast

For the calculation of the demand will work especially with those classified in the group A according to ABC classification. Special forecasting techniques are required for the spare parts. In fact, a common characteristic of the articles in group A of spare parts is their relatively low level of consumption. A component installed in a machine usually requires a replacement, due to breakdown or preventive maintenance, rather sporadically, with intervals of up to several years. In addition, the consumption rate of a spare part depends to a large extent on the number of equipment in which the piece is installed, as well as on its intrinsic level of reliability. All these reasons explain why specific forecasting techniques, different from those traditionally used for production materials, should be applied for maintenance.

If the demand is considered to be a Poisson model, the needs are separated equally for each spare part during the estimated period. Following the approach of the spare part, the requirements of each spare part are considered separately. So the demand for spare parts is equal to the corrective replacements made during the life cycle.

For critical equipment type B, over time the goal is to be using the same strategies as those of type A, although they are not so critical, so they should be calculating the demands of these teams progressively. For the C, it can be more or less strict given its uncritical nature.

3.4 Stock management policy

The goal of any control system is to determine when and how many parts to order. This decision must be made depending on the stock situation, the anticipated demand and the different cost factors. So spare parts can be categorized in the stock as orders in hand, pending orders and delayed orders.

- We must take into account the following factors in the demand model is a Poisson distribution: When there is a demand there are two possibilities. That the spare part is present in the inventory and sent to the maintainers for corrective replacement. And that the spare part is not and that demands an order with delay from the park. So the maintainers will have to wait until the spare arrives the total waiting time.
- When the spare reaches the warehouse there will also be two possibilities. One, that the spare is a late order so it will be sent to the maintenance team immediately. Or, that the spare will remain in the inventory until the order or base stock level arrives.

This approach is used both in the park warehouse and in the plant. Depending on whether the delay occurs in any of the two inventories, a stochastic or deterministic waiting time can be used for the acquisition of the spare part.

3.5 Computation of parameters and inventory costs

Once you have the previous calculations, the inventory parameters are calculated. The first thing is to calculate the time in stock and the time in delay. The objective is to calculate the sum of both times.

At this stage, storage and order costs are also simulated. So you can have the base cost of stock of each spare part. For the cost of storage, the time in stock of the spare is taken into account during the simulated time. And the cost of delay is considered similarly.

3.6 Policy test and validation

As a final phase, the testing and validation of the results achieved by applying the aforementioned steps to reality must be achieved and refinement applied where necessary.

4 JOINT OPTIMIZATION OF LOGISTICS AND MAINTENANCE

In general, maintenance and replacement policies are treated separately or sequentially in the industry. However, since the stock level of spare parts often depends on maintenance policies, it is better to treat these problems simultaneously.

It must be taken into account that the availability of spare parts and their quick access are key to the success of maintenance management systems. Therefore, a logical approach to solve the problem of the availability of spare parts lies in preserving the large size of the inventories of spare parts for immediate disposal when necessary. However, a cost-effective solution to this problem requires a trade-off between overstocking and a shortage of spare parts. For these reasons, designing spare parts optimally represents a critical and important task for production managers.

Van Horenbeek [11] makes a classification using different criteria when classifying the different systems that optimize together logistics and maintenance, defining them in 7 sets of criteria.

In the literature, the most commonly used approaches to develop a possible stock supply decision model are simulation and mathematical programming. Mathematical programming refers to the development of mathematical models based on linear programming, dynamic programming, objective programming, etc. The multi-level technique (Multi-echelon) for Sherbrooke's recoverable elements control model [12] is the first mathematical programming application in the problem of inventory management of spare parts.

Another approach that is commonly used to solve the spare parts management problem in the industrial world is simulation. The main advantage of simulation over mathematical modelling is its ability to describe non-linear multivariate relationships, which can hardly be put into an explicit analytical form. However, simulation modelling is not an optimization technique. If the objective is to develop optimal spare parts inventory policies using simulation, then it is necessary to integrate the simulation model with an optimization technique. In simulation optimization, one or more discrete event simulation models replace the analytical objective function and constraints. The decision variables are the conditions in which the simulation is executed, and the performance measure becomes one (or a function of several) of the responses generated by a simulation model. The classical methods used with the simulation are the surface response methodology, the design of experiments and the stochastic approach.

In recent years, metaheuristics such as genetic algorithms (GA), simulated cooling and taboo search have been widely used together with simulation to improve the efficiency of the search procedure. Among these guided search methods, the optimization of simulation through GA is a fairly active research area. There are successful GA-based simulation optimization applications in scheduling, installation layout, assembly line planning, supply chain management, kanban systems, maintenance policy selection and spare parts inventory management.

The proposed procedure has been implemented in three phases. The first phase involves the development of a discrete event simulation model, which represents the behaviour of the system with its maintenance and aspects related to the inventory. The development of a GA to optimize the control parameters of the spare parts inventory management policy is carried out in the second stage. The last stage involves the integration of GA with the discrete event simulation model integrated in the optimization cycle.

Starting from the base that the mean time between failures (MTBF), the average repair time (MTTR) and the PM durations follow the Weibull distribution and the delivery times follow the triangular distribution.

Therefore, when modelling all stochastic input data, we refer to this data. In addition, we assume that:

- A PM action is performed when the machine is stopped. So, there are no interruptions due to PM.
- There are enough maintenance personnel to carry out the required maintenance activities.

Our objective will also be to obtain a list of materials that currently remain in the warehouse (or that are missing) with their direct influence on the cost.

5 CONCLUSIONS

The maintenance processes try to make use of the knowledge of failures and accidents to achieve the highest possible safety at the lowest cost. This means maximizing the availability and efficiency of the equipment, controlling the degradation, making a safe operation environmentally and for the people, as well as minimizing the total cost of the operation.

The risk-based maintenance methodology (RBM) is designed to study all failure modes, determining the risk associated with each of them, developing a maintenance policy that minimizes the occurrence of high-risk failure modes. In this paper a proposal for a risk calculation methodology has been made, that takes into account the dynamic factors over time, in order to prioritize later maintenance actions based on the current risk.

A methodology for decision making in logistics and maintenance in sequence form with 6 steps has been presented, which solve the main questions that generally arise during the process to define the correct management policy for spare parts.

Finally we consider that the best algorithm to perform the joint optimization of logistics and maintenance is a combination of genetic algorithm that is supported by a Monte Carlo simulation. The proposed algorithm must be implemented in three phases: a discrete event simulation model that represents the behaviour of the system with its maintenance; a GA to optimize the control parameters of the inventory management policy; GA integration with the discrete event simulation model integrated in the optimization cycle.

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8.14 A Hybrid Optimization Algorithm for Standardization of Maintenance Plans

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Resumen

Este artículo presenta un algoritmo para resolver el problema de optimización combinatoria en la definición de planes de mantenimiento preventivo. Este problema no es fácil de resolver, ya que las tareas realizadas en los activos pueden ser redundantes o no requeridas. El objetivo es una definición más precisa de los planes para reducir los costes de mantenimiento, donde se pueden utilizar diferentes algoritmos de optimización. Tomar un solo enfoque de algoritmo de optimización podría servir para encontrar una solución óptima dependiendo del caso de uso, pero no encuentra resultados fiables de manera genérica. El nuevo enfoque híbrido con diferentes tipos de algoritmos muestra que se obtienen mejores resultados que el uso de los algoritmos de optimización individuales.

A hybrid optimization algorithm for standardization of maintenance plans

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Abstract. This paper presents an algorithm to solve the combinatorial optimization problem in the definition of preventive maintenance plans. This problem is not easy to solve, since tasks performed on assets can be redundant or not required. The objective is a more accurate definition of plans to reduce maintenance costs, where different optimization algorithms can be used. Taking a single optimization algorithm approach could serve to find an optimal solution depending of the use case, but it does not find reliable results in a generic way. The new hybrid approach with 4 different algorithms shows that better results are obtained than the use of the individual optimization algorithms.

Keywords: Preventive maintenance, optimization algorithms, planning

1 Introduction

In general, data analysis techniques allow us to improve the way we manage our business. Specifically, through the application of descriptive analytics we can understand in more detail the current state of the business, and predictive analytics estimates what we do not know. Finally, there is a third level of analytics as a natural extension to these processes, prescriptive analytics, which leads to complete integration with the business.

The prescriptive analytics considers not only the business data, also how the decisions affect the costs and benefits accounts, and what restrictions and considerations should be considered in the actions that are going to be carried out. This automatically generates realistic action policies that have a direct impact on benefits.

In many cases, the decision process is not systematic. The decision to be made is framed in a context defined by a series of restrictions. These restrictions set the conditions for a decision to be valid, but there are many valid decisions in the same context. Usually when making these decisions, there is implicit a way of assessing the quality of one decision over another, an objective function that allows to distinguish between a better valid solution and another, also valid, but which is worse.

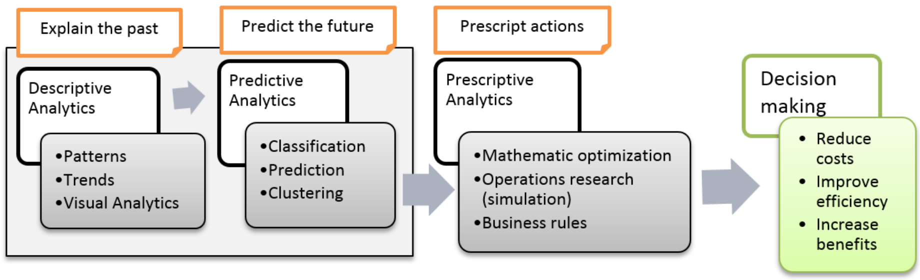

Fig. 1. Prescriptive analytics techniques and benefits.

On the other hand, maintenance research and development is gaining importance worldwide because of the irruption of technologies that enable advanced maintenance solutions, including prescriptive analytics techniques. Maintenance management involves different concepts and activities (Garg & Deshmukh 2006): Part of the literature deals with (a) development and selection of optimum maintenance strategies (Bevilacqua 2000) (Christer 1999) (Gilabert 2015) (Koren 2002) (Scarf 1997); other major areas of research describe (b) the modelling and programming of the machine maintenance (Duffuaa 1999) and (c) the theory of reliability, replacement and the determination of frequency of inspection (Jardine 2001). Finally, other researchers concentrate on (d) simulations to measure a maintenance system (Banks 2005) (Barros 2003).

In this paper our objective is to focus on a problem related to maintenance strategies that is scarcely tackled so far in literature: It is related to the development of standardized maintenance plans related to PM tasks, in complex maintenance scenarios with different fleet characteristics as well as maintenance resources. These scenarios appear in areas such as fleet transport systems (buses, trains), infrastructures, or elevators. Here, Preventive Maintenance (PM) tasks should be identified and developed to manage the failure. PMs are value-added tasks conducted using the least labor, downtime and materials to complete the tasks. Therefore, fleet maintenance requires standardized job plans. And the definition of plans concerning the PM tasks to be done by maintenance crew is a crucial problem prior to resource planning. The development of these plans is not trivial. Product maintenance specifications can include up to one hundred different actions, to be executed with different frequencies, and with some differences depending of product versions. On the other hand, not all maintenance crew is able to execute all actions (some of them may be better reserved to senior specialists) and there may be even different contracts regarding the frequency of inspections depending on the SLA (service level of agreement contracted) or the country legislation, to name only some examples.

These characteristics fits as a challenge for automated decision-making trough expert optimization models. Decision making tools help users to improve the ability of solving problems and the capabilities of production systems (Medina-Oliva 2015) (Molenaar 2001). Optimization is also linked to decision-making, minimizing the maintenance costs or the ecological impact (Jiang et al 2018). In this case, the standardization of maintenance plans cannot be solved usually by accurate optimization algorithms, which are those that guarantee finding an optimal solution. What disables the application of accurate optimization algorithms to these problems is the computation time. This fact has a consequence in the scientific community: it is the born of meta-heuristics techniques. Despite not finding the optimal solution, these techniques ensure that there is a good solution with the advantage that this search could be carried out in a reasonable execution time. Therefore, depending on the needs, there can be multiple optimization criteria simultaneously. It is possible to have different optimization systems or include commitments for calculations with partially connected criteria.

The rest of this paper is organized as follow. Section 2 introducing the problem of standardization of maintenance plans. Section 2 shows the proposed hybrid architecture and the specific algorithm inside. Section 4 presents the experimentation of the solution. Finally, the conclusions are given by integrating also future research directions.

2 Standardization of maintenance plans

The optimization methods addressed to tackle this problem that appears in literature are varied: Some of the optimization criteria are related to smoothing the preventive maintenance work load of the crew (Ben-Daya 2009), other related to short-term (Dedopoulos 1995) and long term (Garg 2006) scheduling of planned maintenance work. Hybrid optimization has been also used in maintenance for determining periodic inspections (Phan & Zhu 2015). Instead, this paper is centered in optimizing the group of tasks to be done by the maintenance crew in a fleet, taking into account that having too much different task plans could be difficult to be managed by the staff.

A maintenance plans is defined as a set of multiple tasks of short duration. For instance, in case of a car could be (a) check tire pressure, (b) change oil and filters, and many other tasks with a defined duration and frequency. The definition and realization of these tasks depend on the configuration of the assets, applying also the corresponding legislations. Theoretically the optimal solution would consist on defining a different maintenance plan for each specific asset. In any case, that solution is not feasible, since the operators in charge of performing maintenance tasks cannot have a specific plan for each asset. A more efficient solution is to define a single plan (or a reduced set of plans) because the worker can perform the tasks efficiently. For this reason, maintenance plans must be standardized for all assets in a system, even if this implies the execution of tasks that are not strictly necessary on certain assets.

Several maintenance factors or policies have an influence and must be considered when making the definition of the plans. These considerations suppose a problem of combinatorial optimization. The optimization problem must take into account the following factors, considering that it applies to a set of assets of a similar nature:

- Asset configuration: Each asset has a set of tasks to execute depending on its configuration.
- Tasks and frequency: Each task has a minimum frequency which depends on different legislations, safety criteria or customer requests.
- Client contract: The asset belongs to a client, that depending on the contract can have certain additional tasks (e.g. cleaning) or tasks that are made more frequently.

- Plans: The tasks to be executed on an asset are grouped in different plans, due to their different frequency requirements.
- Visits: The maintenance of an asset requires N plans carried out in V visits and by a certain operator skill. Obtaining the number of visits associated with each plan is another optimization problem.
- Worker profiles: the worker preform some tasks depending on their skills.
- Maximum plan duration.
- Balance parameter: the maximum difference of minutes between plans.

3 The hybrid algorithm

The hybrid algorithm tries to solve two different optimization problems. On the one hand, searching the best combination between plans and visits. Input data only provides the total number of plans and visits related to the asset. For instance, the requirements could be 2 plans in 6 visits, and the algorithm must give as a result that Plan 1 should be done in 2 visits and Plan 2 in 4 visits (or maybe other combination as 1-5 or 3-3). On the other hand, the hybrid algorithm searches the best standardization of tasks in the plans/visits to perform, according to the input requirements.

Figure 2 depicts the algorithm architecture used in the hybrid optimization. During the optimization, the tasks are distributed in the maintenance plans, which have previously been assigned a certain number of visits. This process is done in 4 different algorithms, obtaining as a result the best plan provided after the execution of:

1. Rules procedure minimizing time.
2. Rules procedure balancing plans.
3. Greedy algorithm minimizing time.
4. Greedy algorithm balancing plans.

The main reason of using a hybrid approach is due to 2 different objectives are managed at the same time:

- The minimization of the total time required to perform the plan on the asset, that is, the sum of all tasks in visits, in every plan.

$$min \sum_{i=1}^{i=n} \sum_{j=1}^{j=m} t_j v_i \tag{1}$$

where n is the number of plans, m the number of tasks related to plan i, t_j the duration of task j, and v the number of visits of plan i.

- The minimization among the differences in duration of plans (maximum balance)

$$\min\left(\left(\max_i \sum_{j=1}^{j=m} t_j v_i\right) - \left(\min_i \sum_{j=1}^{j=m} t_j v_i\right)\right) \tag{2}$$

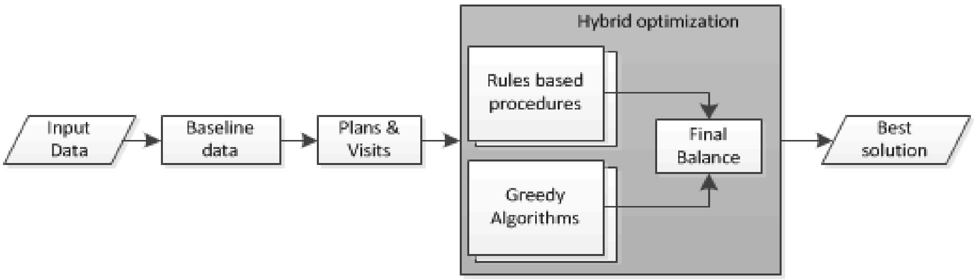

Fig. 2. Hybrid optimization algorithm architecture.

Next main parts of the algorithm are described in detail.

3.1 Baseline data

During the first step the input information must be provided to perform the optimization. In detail:

- Main asset configuration. The concept of a plan standardization is not to provide the specific configuration, but it should be defined in an upper level (e.g. in case of cars, they could be gas or diesel, involving different maintenance tasks).
- Country legislation. Usually countries specify different frequency inspections related to maintenance tasks.
- Client contract type, the levels of SLA. For instance: Low cost, Normal and VIP.
- Worker profiles, in relation with their skills. For instance, Technician and Specialist.
- For each worker profile, number of maintenance plans and total visits by year.
- Maximum duration of a maintenance plan, in minutes.
- Maximum difference among plan durations in minutes (B), in order to provide balanced plans.

According to the previous inputs, the baseline data is obtained. This data consists on a set of tasks and their compulsory visits for each task. The Optimal Time is defined as the sum of these task durations multiplied by their visits.

$$OT = \sum_{i=1}^{i=m} t_i \, v_i \tag{3}$$

where m is the total number of tasks, t_i is the duration of the task and v_i the minimum number of visits of t_i. This Optimal Time will be used for validation purposes. The evaluation criterion is defined as the difference between the Total Time and the Optimal Time.

3.2 **Plans Vs Visits**

As introduced before, obtaining the number of visits associated with each plan is another optimization problem. The maintenance of an asset requires N plans carried out in V visits and by a certain operator skill. This is calculated by another instance of the hybrid optimization algorithm. However, this execution is performed in a small number of iterations (< 10).

The target of Plans & Visits process consists in selecting the most appropriate plans/visits relation so that the search is more limited, and the search algorithm starts from a defined configuration. The step in this process starts with the calculation of all possible combinations of visits and plans by operator profiles. For example, for an expert profile, 3 plans and 6 visits (Expert-3-6), the number of visits of each plan could be: 1-1-4; 1-2-3; 2-2-2. For each possible combination, the hybrid algorithm with 10 iterations is executed. The best result obtained (E.g. 1-2-3), is the configuration used in the next step.

3.3 **Rules Procedures**

This first procedure follows this sequence:

- Tasks are ordered from largest to smallest duration.
- Sequentially, each task is assigned to a plan, using this algorithm:
  - Selection of possible candidate plans: do not include the task previously and meet the operator profile requirement.
  - Select the plan where the number of times matches the number of visits of the task, or in its absence the smallest absolute difference.
  - In case of a tie, the plan with the minor number of visits is selected.

The second procedure follows a similar sequence, except in case of tie in last step: the plan with the minor duration is selected in this case. This change produces a more balanced result.

3.4 **Greedy algorithms**.

The greedy algorithms are based on covering the complete space of possible solutions to the problem. We have selected the backtracking algorithm. This technique is the direct application of the search method known as first in depth. The algorithm consists on:

1. Select an option among the possible ones.
2. For each selection, consider every possible option recursively, in a loop (search in depth).
3. Return the best solution found of all evaluated solutions.

In our case, the first greedy algorithm performs this sequence:

1. If a task can be carried out by several profiles, all the possibilities are considered.

2. Combinatorial search of assignment of all possible tasks to each visit is done. That is, a visit could be considered as an empty box where the different combination of tasks is inserted.

The second greedy algorithm is similar except it works with sorted visits: in each search iteration, the visits are sorted by their absolute difference between the number of visits of the task and the number of visits of plan, prioritizing a maximum balance among the plans

3.5 **Final Balance**.

The Final Balance consists of 2 procedures which works with the found solution, trying to improve it. The final balance follows this sequence:

1. A greedy algorithm that tries to remove the tasks of the plans that exceed the maximum allowed or the longest in case of not having it. It moves them to the plans of shorter duration.
2. If the flattening criterion (B) is not yet met, another greedy algorithm adds unrealized tasks to the plans of shorted duration. This Final Balance is applied in the execution of the 4 algorithms implemented.

4 Use case

The hybrid algorithm has been validated using truck forklift fleet job standardization. In this use case are considered two of forklifts in a fleet: electrical and diesel. Also the maintenance crew is categorized into specialists and technicians. Due to a user requirement, a short execution time is needed, and the execution of greedy instances has been limited to 1000 iterations, enabling an execution time minor than 2 minutes. Moreover, two different experiment have been done.

In the first experiment, the country evaluated has a lot of diversity in maintenance plans, and the maintenance company needs to standardize the plans to solve the problem of diversity. The frequency of maintenance is set to 2 months, by one specialist. The optimization has been executed setting 3 plans at 3 minutes of maximum difference in duration (B=3). The Optimal Time (OT) is 82.57 m. Table 1 provides results when the greedy algorithm is isolated from previous rules procedures.

Table 1. Greedy algorithm isolated in Specialist-2-6

Skill	Plan	Visits	Duration(m)
Specialist	#1	1	19.14
Specialist	#2	2	18.46
Specialist	#3	3	18.07

Annual total time: 110.27 m.
Difference OT: + 27.70 m.

However, when using the hybrid algorithm, the annual total time for maintenance is almost 2 minutes shorter.

Table 2. Hybrid algorithm result in Specialist-2-6

Skill	Plan	Visits	Duration(m)
Specialist	#1	1	18.10
Specialist	#2	2	18.71
Specialist	#3	3	17.60

Annual total time: 108.32 m.
Difference OT: + 25.75 m.

The usage of this hybrid optimization algorithm improves the results comparing the usage of just a greedy algorithm, and even the computational time is improved. Actually, the standardization of plans using the final result in Table 2, supposes an increase of 7% in annual total time maintenance, and therefore a similar increase in maintenance costs, but the company consider this as an indirect cost required that allows to save money in learning, reduce human mistakes caused by having too much different plans and simplify maintenance planning for maintenance crew load balancing.

In the second experiment considers the situation where specialist executes the maintenance every month during a year, setting only 2 different plans. In an annual maintenance, the first plan is executed every 6 months and the second one the rest of months. OT is 261.88 minutes. The initial results are shown in Table 3.

Table 3. Specialist-2-12

Skill	Plan	Visits	Duration(m)
Specialist	#1	10	18.65
Specialist	#2	2	42.7

Annual total time: 271.91 m.
Difference OT: + 10.03 m.

In this case the objective is to save money using two types of workers (specialist and technician). In this case the specialist executes 2 plans every 6 months, and the technician executes 1 plan in 10 visits, setting a maximum difference among plan durations of 1 minute by profile (B=1). Table 4 shows how the expert skill improves the time while keeping the basic tasks duration, related to previous situation in Table 3.

Table 4. Specialist -2-12; Technician -1-10; B=1

Skill	Plan	Visits	Duration(m)
Specialist	#1	1	38.85
Specialist	#2	1	38.53
Technician	#3	10	18.65

Annual total time: 261.88 m.
Difference OT: 0 m.

This result means an improvement of 10 minutes by truck. Assuming a truck fleet of 100 units and considering that technician cost/hour is 40% less than using the specialist worker, the savings are close to 32% in this case.

5 Conclusions

In an optimization problem, a hybrid approach improves the results obtained in comparison with the use of one single algorithm. This paper presents a new algorithm to solve the combinatorial optimization problem in standardization of maintenance plans, using a hybrid approach with 4 different algorithms. The usage of this algorithm allows to reduce costs or to enable an easier later planning. This algorithm is completely scalable in number of tasks, plans, visits and operator profiles. The hybrid combinations have been implemented in a multi-stage process. However, after this work we considered that it is possible to take advantage of the combination of algorithms in other ways, for instance, using a hierarchical approach. Next step will consider an Estimation of Distribution Algorithm (EDA) on the top, that will be fed by the optimal results found by 4 different kind of optimization algorithm: Rule-based, greedy, evolutionary and simulated annealing. The future objective will be to improve this algorithm expanding both the optimization typologies and the way to combine their results.

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