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Aplicación de modelos matemáticos para el mantenimiento predictivo

MEMORIA QUE PARA OPTAR AL GRADO DE DOCTOR EN INFORMÁTICA PRESENTA

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Resumen

La importancia del mantenimiento de cualquier subsistema ha aumentado en importancia tanto para el sector industrial como para el científico. Las empresas pretenden mejorar sus técnicas de mantenimiento para aumentar la vida útil de sus equipos. Todos los equipos se degradan con el tiempo, ya que funcionan bajo una determinada carga o voltaje en el entorno real, provocando la necesidad de actividades de mantenimiento más asiduamente a medida que envejecen.

Existen tres tipos de mantenimiento y la historia demuestra que poco a poco el tipo de mantenimiento más común está siendo el más complejo. Al principio el único mantenimiento conocido era el mantenimiento correctivo, aquel que se produce tras un fallo o parada de máquina. Conforme se adquirieron conocimientos sobre el proceso y las máquinas, los operarios que en ellas trabajaban fueron adquiriendo conocimientos sobre patrones de comportamiento de las mismas y se fue evolucionando a un mantenimiento preventivo, donde el mantenimiento se realiza de forma periódica y previa a un fallo. Recientemente este mantenimiento ha evolucionado debido a los avances en la tecnología y la llegada de la industria 4.0, dando cabida al mantenimiento basado en condición, el cual se caracteriza por programar mantenimientos en función de la degradación en la que se encuentre el subsistema.

La presente memoria de tesis presenta una revisión sobre la actividad de investigación aplicada que se ha realizado mediante varios proyectos relacionados con el mantenimiento predictivo asociado a procesos industriales. Uno de los resultados principales es la realización de una herramienta web que permite al operador consultar el tiempo estimado hasta el fallo en un proceso de mecanizado y junto a ello un histórico de datos del sistema.

Se han obtenido otros resultados que generan una evolución en el mantenimiento de los sistemas estudiados, lo que reduce el coste y aumenta la productividad de estos. Para ello se han aplicado metodologías híbridas donde el objetivo principal radicaba en la creación de una metodología de mantenimiento predictivo para cada uno de los procesos y en algún caso la posibilidad de generalización de la misma a procesos similares.

Agradecimientos

Mucho tiempo ha pasado desde que este proyecto de tesis comenzó. Desde aquel Lunes 7 de Marzo de 2016 en TECNALIA del SUR. En esos primeros días, donde todos nos imaginábamos el día de hoy, alguien me dijo: ”todo comienzo tiene un final”. Y aquí estamos, al final de este camino. Un camino que aunque a veces pudiera parecer estar recorriendo solo, nunca fue así. Y es a todas aquellas personas que en mayor o menor medida me han acompañado a quienes quiero darles las gracias. Nunca llueve a gusto de todos y pido disculpas a todos los que pudieran sentirse desplazados pero quiero remarcar la labor y el apoyo de aquellos que han estado en el día a día e involucrados en el proyecto. Como bien sabéis soy parco en palabras, pero dada la situación, intentaré expresarme un poco más en estas lineas.

Mi primer y mayor agradecimiento es a mi director, mi maestro, mi sensei en la analítica de datos. Aquel que desde que pisé por primera vez una sede de Tecnalia y sin conocerme de nada se ha preocupado de que esto avanzara, se ha preocupado de que yo estuviera bien, de que pudiera centrarme en ello. Muchas veces desde la sombra y sin llamar la atención, pero siempre ahí. En estos 5 años hemos trabajado juntos, asistido a congresos juntos, incluso nos hemos ido de sidrería. Realmente no sé cómo darte las gracias por todo ello, sin tu ayuda ninguno de los dos podría leer estas lineas.

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Cambiando de ámbito y ya sumando agradecimientos a aquellos que también me han apoyado, aún sin saber muy bien lo que he estado haciendo (porque de esos hay unos cuantos), no puedo evitar pensar en primer lugar en aquellos que ya no están. Aquellos que separaron su camino del mio pero que estarán siempre presentes en todas en mis publicaciones. Aquellos que me vistieron de rojo y blanco por primera vez, con los que he ido a recoger caracoles hasta perderme por el monte, que nos contaban que las salchichas corrían por los platos y mil historias y aventuras que no es momento de contar. También agradecer a los dos jóvenes que han compartido el día a día conmigo durante gran parte de esta aventura. Nunca olvidéis dejar alguna **puerta abierta**, por lo que pueda pasar.

Por último pero no menos importante, merecen mención todas aquellas personas que han hecho estos 4 años más llevaderos, esto es, todos aquellos con los que he compartido eventos sociales: ya sean vacaciones en la otra punta del mundo, barbacoas, bodas, comidas, cenas de equipo, despedidas de soltero, paseos por el monte, fines de semana de desconexión, actividades deportivas varias, cervezas belgas y un largo etcétera. Porque cada experiencia nos define y cada persona con la que lo compartimos nos influye. Soy así gracias a vosotros.

Brindaremos por este objetivo cumplido “mirando a las estrellas” y poniendo el punto de mira en algún punto un poco más alto. Siempre creciendo a vuestro lado.

Gracias Jóvenes

Índice general

Parte I

INVESTIGACIÓN REALIZADA

CAPÍTULO 1

Contexto de la actividad investigadora

1.1. Motivación

Conocí Tecnalia Research & Innovation (en adelante Tecnalia) cuando me encontraba terminando mi Grado en Físicas en la Universidad del País Vasco (UPV/EHU). Al comenzar el máster en Ingeniería Computacional y Sistemas Inteligentes en la Universidad del País Vasco (UPV/EHU) surgió la posibilidad de realizar prácticas. Ese año, bajo la tutela de Fernando Boto, di mis primeros pasos en la resolución de problemas complejos y reales mediante técnicas de análisis de datos, algo que me apasionó desde un primer momento. Así comenzó mi andadura en los temas de análisis de datos. Una vez terminadas las prácticas, desde Tecnalia se me planteó la posibilidad de continuar con la investigación y aplicación de algoritmos a problemas complejos mediante una beca de doctorado. Aunque en mis planes iniciales no contemplaba la realización de una tesis doctoral, la posibilidad de seguir formándome en el análisis de datos junto a grandes profesionales de la materia hizo que no dudara en aceptar este reto. Me dispuse entonces a compaginar el doctorado en la Universidad del País Vasco (UPV/EHU) junto con la actividad laboral en Tecnalia. Los proyectos asociados a mi actividad han sido en su totalidad soportados por Tecnalia, siempre relacionados con el análisis de datos en procesos industriales complejos y bajo la supervisión tanto de Fernando Boto (Tecnalia) como de Itziar Irigoien (UPV/EHU).

Tras esta breve descripción cronológica y contexto de cómo he llegado a este punto, en los siguientes capítulos y apartados se presentarán y discutirán los proyectos y las contribuciones relacionadas en las que se ha trabajado en este proyecto de tesis. Este proyecto de tesis es el resultado de la investigación en el contexto de la fabricación industrial en Tecnalia con la colaboración del departamento de Ciencia de la Computación e Inteligencia Artificial (CCIA) de la UPV/EHU.

1.2. Tecnalia

Las actividades descritas en este proyecto de tesis han sido desarrolladas en Tecnalia. Tecnalia[1] es un centro tecnológico privado, independiente y sin ánimo de lucro de excelencia internacional. Tecnalia es el centro tecnológico privado líder en España y uno de los más importantes a nivel europeo, con una plantilla de 1.407 personas (de las cuales 248 tienen al menos un Doctorado) y unos ingresos de 110 Millones € en 2018.

Un rasgo diferencial de Tecnalia es su innovador modelo operativo basado en Divisiones interconectadas entre sí. Esta forma de trabajar la capacita para afrontar cualquier reto tecnológico ya que este engranaje de cooperación funciona gracias a la transversalidad de equipos, proyectos y clientes que colaboran entre ellos aunando experiencia y compromiso. La especialización de Tecnalia se refleja en las 6 grandes divisiones que abarcan todos los ámbitos de investigación e innovación de la sociedad. Las Divisiones orientadas al cliente y especializadas por sectores de actividad son Energía y Medio Ambiente, Industria y Transporte, ICT, Salud y Construcción Sostenible que se ven respaldadas por la División de Servicios Tecnológicos.

La división de Industria y Transporte se centra en el diseño, la fabricación y el mantenimiento de productos y servicios industriales, para la mejora de la competitividad de sus clientes en los siguientes sectores estratégicos: fundición y siderurgia, máquina-herramienta, automoción, aeroespacial, aeronáutica, ferrocarril, construcción y des-fabricación. En términos más concretos, y estrechamente relacionado con las tareas del proyecto, el área de Instrumentación y Sistemas Inteligentes (donde se ha realizado este proyecto de tesis) centra su actividad en:

- sistemas de instrumentación y adquisición de datos para maquinaria y bienes industriales.
- fábrica digital: supervisión de la producción, optimización y control óptimo del proceso.
- soluciones de vigilancia basadas en la condición para el mantenimiento y la gestión del ciclo de vida de los productos.
- sistemas de seguridad industrial y gestión de riesgos.
- soluciones de eficiencia energética centradas en modelos de predicción del consumo y herramientas de apoyo a la toma de decisiones.

Actualmente, la sociedad desarrolla su actividad en un entorno dinámico en el que la demanda de que los sistemas industriales e infraestructuras sean fiables y robustos se viene incrementando día a día. Los fallos o interrupciones no son aceptables. Esta situación ha traído a un primer plano el mantenimiento como parte fundamental de la estrategia de los gestores de infraestructuras e instalaciones industriales. El mantenimiento es un proceso que se basa en la obtención de información, por lo que, teniendo esto en cuenta, el planteamiento de Tecnalia en este ámbito se centra en el desarrollo de herramientas y tecnologías que den respuesta a las necesidades industriales a través de la fusión de datos y conectividad transparente. El objetivo final es facilitar la integración sin barreras de sistemas y equipos, el procesado de datos que contengan información sobre el estado de los sistemas y la reconfiguración del estado de los equipos de trabajo para conseguir los objetivos de producción fijados. El objetivo de Tecnalia en el ámbito del mantenimiento es por lo tanto "facilitar las operaciones de inspección y mantenimiento de instalaciones y máquinas con soporte

[1] www.tecnalia.com

de tecnología predictiva y herramientas de visualización, consiguiendo un mejor rendimiento de los procesos productivos, así como un ahorro en tiempo y costes en la asistencia técnica y mejorar la rentabilidad y eficacia en las empresas".

Alineado con este objetivo se ha creado en el 2017 un Equipo de Relevancia Tecnológica (*ERT*) denominado Maintenance 4.0 dentro del cual se ha desarrollado el trabajo de este proyecto de tesis. Los *ERT* son una herramienta de excelencia dentro de la estrategia de Tecnalia en sectores o líneas de actividad consideradas claves por el centro. El alcance de las actividades de investigación del Equipo de Relevancia Tecnológica Maintenance 4.0 de Tecnalia cubre distintas áreas de ingeniería, ciencias básicas y aplicadas y de gestión, dirigidas a generar soluciones de ingeniería integradas para el mantenimiento de sistemas industriales. El grupo de trabajo posee y continúa desarrollando competencias en el campo de la operación y el mantenimiento (*O & M*, Operation and Maintenance), con un foco especial en fiabilidad, disponibilidad, mantenimiento y seguridad (*RAMS*, Reliability, Availability, Maintainability and Safety), mantenimiento basado en condición (*CBM*, Condintion Based Maintenance) y *e-Maintenance*.

1.2.1. Líneas estratégicas del grupo del equipo de trabajo

La aplicación efectiva de la teoría y práctica del mantenimiento se realiza para compensar la limitación en fiabilidad y devolverlo al nivel deseado incorporando en el proceso los aspectos tecnológicos y económicos. El concepto de Mantenibilidad que se usa en Tecnalia, asume los aspectos relativos al mantenimiento desde las etapas de diseño, con el objetivo último de facilitar estrategias de mantenimento fáciles de implementar y "cost effective" de forma que se pueda asegurar los niveles exigidos de fiabilidad. Las acciones de mantenimiento, si se implementan de la manera adecuada, pueden controlar la degradación y reducir y hasta eliminar la probabilidad de ocurrencia de fallos, además de restaurar un sistema caído a su estado operacional óptimo.

Fiabilidad, disponibilidad, mantenibilidad y seguridad (RAMS4) es una metodología que aborda la preservación de la función y la prevención de fallos durante las fases de diseño y operación del ciclo de vida de un activo. El objetivo final de un programa de RAMS4 es suministrar una plataforma para integrar y dar soporte a las tecnologías y competencias relevantes, que faciliten la transferencia de este conocimiento desde el entorno de la investigación aplicada hacia diferentes sectores industriales.

La investigación que se lleva a cabo en Tecnalia sobre aspectos de monitorización de la condición y mantenimiento basado en la condición incorpora desarrollos de métodos y modelos para evaluar el estado de un sistema o componente, usando datos obtenidos tanto on-line como off-line del sistema o componentes de interés. Esta es la línea de investigación principal tratada en este trabajo.

Igualmente los conceptos de diagnosis y la prognosis son dos aspectos importantes en un programa CBM. La diagnosis aborda la detección, aislamiento e identificación de un fallo cuando este sucede. Por otro lado, una aproximación desde la prognosis trata de obtener una predicción del fallo antes de que ocurra y pretende determinar si un fallo es inminente así como estimar en cuánto tiempo y cuánta probabilidad de suceder tiene. El diagnóstico es un análisis posterior del evento, y conducirá normalmente a una acción de mantenimiento correctivo, mientras que la prognosis es un análisis anterior al evento que deberá resultar en acciones preventivas. Dentro del marco de trabajo de un programa CBM, los esfuerzos de Tecnalia se fijan no solo en el desarrollo de métodos y modelos, sino que también trabajamos para avanzar en la explicación científica de los mecanismos de degradación que conducen a los fallos. De la misma manera se trabaja en el desarrollo de tecnologías para capturar los grados de degradación y evaluar el estado del activo en tiempo real.

El concepto tras el programa de investigación e-Maintenance es facilitar la investigación, resultados y formación en actividades de mantenimiento y operación, mediante el desarrollo de herramientas avanzadas para la minería de datos y la analítica de datos. El propósito desde Tecnalia es apoyar a la industria de forma que puedan implementar la arquitectura e-Maintenance y poder acceder y usar el conocimiento experto y conocimientos de Tecnalia en sus programas de innovación y mantenimiento.

La estrategia se basa en la generación de activos tecnológicos (por ejemplo frameworks, herramientas, metodologías y tecnologías) alineados con las prioridades de la industria y focalizados en conceptos como Data Fusion, Information Sharing, Seamless Connectiviy y Distributed Realtime Data Processing. Estos activos abordan desafíos tales como la conectividad entre dominios, capacidad de comunicación e interoperabilidad entre la infraestructura y sistemas, fusión de datos, gestión de datos de mantenimiento, calidad de datos, visualización de la información y capacidades de análisis en tiempo real, entre otros.

1.3. Facultad de Informática, UPV/EHU

Este proyecto de tesis doctoral se ha desarrollado en colaboración con la Facultad de Informática de la UPV/EHU y más concretamente con el departamento de Ciencia de la Computación e Inteligencia Artificial (*CCIA*). En particular se ha trabajado en colaboración con el grupo de investigación RSAIT (Robotika eta Sistema Autonomoen Ikerketa Taldea). La investigación del grupo se centra en la robótica móvil donde la aplicación de técnicas estadísticas y de aprendizaje automático son esenciales para el aumento de la autonomía de los robots. Por ello, el grupo también investiga en el mismo ámbito del aprendizaje automático, desarrollando e implementando nuevos enfoques y métodos. Por ello, la colaboración con este grupo de investigación ha sido importante en el desarrollo de este proyecto de tesis.

1.4. Luleå University of Technology

Durante la realización de este trabajo se realizó una breve estancia en Luleå University of Technology (LUT) en el departamento de Operación, Mantenimiento y Acústica. Esa estancia fue inferior a 3 meses y las circunstancias vividas recientemente no permitieron la vuelta a LUT según lo establecido inicialmente. La colaboración iniciada durante la estancia se mantiene y sigue el contacto entre los dos centros, LUT y Tecnalia.

1.5. Objetivos

Este proyecto de tesis se centra en la mejora del mantenimiento en procesos industriales reales. El principal objetivo es la evolución del mantenimiento actual en estos procesos. Es decir, evolucionar de un mantenimiento correctivo o preventivo, normalmente basado en experiencia, a un mantenimiento predictivo.

La evolución de un mantenimiento preventivo a uno predictivo es altamente dependiente de la información que se tiene del proceso y por tanto no existe una única metodología para la obtención del mismo. En este trabajo se plantean distintas alternativas en función de los procesos que se trabajan. Desde regresiones polinómicas hasta modelos híbridos pasando por redes neuronales, máquinas de vectores soporte, etc. siendo un objetivo transversal de este trabajo el encontrar para cada problema la metodología que mejor responde a las necesidades del mismo.

En particular, uno de los objetivos planteados es conocer cómo se relacionan el desgaste de una herramienta de un proceso de mecanizado en función de las características de los materiales mecanizados así como de las condiciones experimentales del mecanizado. De esta manera, se podrá predecir el tiempo de vida útil de la herramienta y planificar su recambio en consecuencia, permitiendo pasar de un mantenimiento preventivo a uno predictivo.

Además, en un problema de máquina herramienta planteado en este proyecto de tesis se requiere de la obtención de un modelo de series temporales para detectar una tendencia y así el tiempo/número de piezas restantes para llegar a un límite determinado. Los datos adquiridos durante el proceso se deberán caracterizar y filtrar de tal forma que luego permitan aplicar los modelos adecuados y predecir el tiempo hasta fallo. Modelos de series temporales como *ARIMA*, Random forest, Gradient boosting, etc. son muy utilizados en éstos ámbitos y son los que se trabajarán para la predicción del número de piezas restantes.

Es también objetivo de este proyecto de tesis buscar la generación de datos sintéticos para aumentar el número de datos disponibles y para evitar tener datos no balanceados. Este problema surge en los procesos donde no se pueden alcanzar ciertos estados y por tanto la adquisición de datos de los mismos es pequeña o nula. Normalmente estos estados que no se pueden alcanzar suelen estar relacionados con fallos o faltas en los sistemas estudiados y no son observables por el coste o incluso por el riesgo que implican. En estos casos se desarrollará una metodología compleja basada en la hibridación de conocimiento experto y datos adquiridos. En particular se buscarán variaciones en determinadas características de señales reales que vienen descritas en la literatura. Además se plantea cubrir la necesidad de mejorar los modelos de predicción generados y se realiza una hibridación o ensemble (conjunto de modelos) de los mismos. Esta hibridación se desarrolla con el objetivo de preservar las cualidades de los modelos y disminuir sus debilidades.

1.6. Publicaciones

En este apartado se detallan las publicaciones obtenidas a lo largo del proyecto de tesis doctoral. Aquellas en negrita muestran las publicaciones relacionadas con el estudio. El resto de publicaciones no están directamente relacionadas pero se han incluido ya que han contribuido a los contenidos de esta memoria.

- Alberto Jimenez Cortadi, Itziar Irigoien, Fernando Boto, Basilio Sierra, Alfredo Suarez, Diego Galar. **A statistical data-based approach to instability detection and wear prediction in radial turning processes**. *Eksploatacja i Niezawodnosc-Maintenance and Reliability*, 20(3):405–412, 2018.

- Alberto Jimenez-Cortadi, Itziar Irigoien, Fernando Boto, Basilio Sierra, and German Rodriguez. **Predictive maintenance on the machining process and machine tool**. *Applied Sciences*, 10(1):224, 2020.

- Fernando Boto, Zigor Lizuain, and Alberto Jimenez Cortadi. **Intelligent maintenance for industrial processes, a case study on cold stamping**. In International Joint Conference SOCO2017-CISIS2017-ICEUTE2017 León, Spain, September 6–8, 2017, Proceeding, pages 157–166. Springer, 2017.

- Alberto Jiménez, Fernando Boto, Itziar Irigoien, Basilio Sierra, and Alfredo Suarez. **Stability analysis of radial turning process for superalloys**. *Management Systems in Production Engineering*, 25(3):158–162, 2017.
- Alberto Jimenez Cortadi, Fernando Boto, Itziar Irigoien, Basilio Sierra, and Alfredo Suarez. **Instability detection on a radial turning process for superalloys**. In International Joint Conference SOCO2017-CISIS2017-ICEUTE2017 León, Spain, September 6–8, 2017, Proceeding, pages 247–255. Springer, 2017.
- Asier González-González, Alberto Jimenez Cortadi, Diego Galar, and Lorenzo Ciani. Condition monitoring of wind turbine pitch controller: A maintenance approach. *Measurement*, 123:80–93, 2018.
- Alberto Jimenez-Cortadi, Fernando Boto, Itziar Irigoien, Basilio Sierra, and German Rodriguez. **Time series forecasting in turning processes using arima model**. In International Symposium on Intelligent and Distributed Computing, pages 157–166. Springer, 2018.
- Submitted Alberto Jimenez-Cortadi, Alberto Diez-Olivan, Itziar Irigoien, Dammika Seneviratne, Itziar Landa-Torres, Iñigo Reiriz-Irulegui, Fernando Boto, Orlando Peña, Iñaki Garcia, Marc Vila and Diego Galar. **A hybrid approach for synthetic data generation and advanced prognostics.**. IEEE TRANSACTIONS and JOURNALS, 2020.

CAPÍTULO 2

Estado del Arte

En este apartado se revisa la literatura existente dentro del ámbito del mantenimiento, focalizándose principalmente en las técnicas de *Machine Learning* asociadas al mantenimiento predictivo. Éstas técnicas se explican brevemente y se muestran varias de sus aplicaciones. Tras esta revisión se presentan las aportaciones científicas realizadas durante el transcurso de este trabajo.

2.1. Mantenimiento

El mantenimiento en ingeniería se refiere a cualquier acción técnica o administrativa, o una combinación de ambas, que permita mantener los activos de ingeniería en, o devolverlos a, sus estados funcionales (Institution, 1984). Desde la revolución industrial, el mantenimiento ha ido adquiriendo protagonismo en la industria. A medida que las máquinas se volvían más complejas, el numero de reparaciones crecía y con ello surgían los primeros departamentos de mantenimiento. No fue hasta después de la segunda guerra mundial cuando los departamentos de mantenimiento empezaron a encargarse no solo de arreglar fallos sino también de intentar evitarlos.

La tecnología también ha representado un gran cambio en el mantenimiento, con la entrada de nuevas técnicas de mantenimiento. Hoy en día, cada empresa adapta las técnicas de mantenimiento para sus propias necesidades y aquellas que funcionan en unas no necesariamente lo hacen en otras. Principalmente se diferencian tres tipos de mantenimientos: *mantenimiento correctivo*, aplicado a encontrar un fallo en el proceso. Normalmente este mantenimiento se realiza en procesos cuyo tiempo de mantenimiento y gasto sean pequeños. El *mantenimiento preventivo* se basa en la programación de paradas de mantenimiento basados en el tiempo medio a fallo de los componentes. Y por último el *mantenimiento predictivo* tiene como objetivo la detección previa de fallo en los componentes y la prevención de su ocurrencia mediante la realización de mantenimientos adecuados. En los siguientes apartados se va a explicar de forma más detallada cada tipo de mantenimiento.

2.1.1. Mantenimiento correctivo

El mantenimiento correctivo se refiere a aquellas actividades realizadas en un sistema para devolverlo a la normalidad de su funcionamiento. Este mantenimiento se realiza una vez el fallo ha aparecido en el sistema (Wang et al., 2014). El mantenimiento correctivo se realiza tanto de manera planificada como no planificada. Generalmente se realiza en pequeños componentes cuyo recambio no supone un gran coste temporal ni económico (Galar and Kumar, 2017) aunque también puede ser necesario en grandes componentes cuya rotura no haya sido prevista. El mantenimiento correctivo requiere de la parada del sistema para la sustitución del componente, lo que aumenta los costes y reduce la productividad. Puede suponer además un gran coste en daños por la interrupción abrupta de los componentes implicados en el mal funcionamiento y otros de la cadena de producción.

2.1.2. Mantenimiento preventivo

El mantenimiento preventivo es un tipo de mantenimiento planeado en un horizonte temporal que pretende prevenir las averías o fallos (roturas,desgaste, corrosión, abrasión,..). El mantenimiento puede ser planificado como resultado de una inspección periódica (Misra, 2008) o mediante el conocimiento experto del sistema . La falta de un mantenimiento preventivo óptimo tiende a aumentar los costos dedicados a las reparaciones debido a la aparición de fallos y la necesidad de implementar un mantenimiento correctivo (Hukka and Katko, 2015). El aumento de los costes dedicados a las reparaciones y averías puede disminuir la productividad del sistema, así como conllevar riesgos ambientales y sociales. En este sentido, el mantenimiento preventivo, planifica tareas para mantener el equipo en condiciones óptimas, es necesario para reducir las roturas inesperadas y, en consecuencia, reducir el costo de las reparaciones (Hendricks et al., 2018).

2.1.3. Mantenimiento predictivo

El mantenimiento predictivo tiene como principal objetivo la reducción del número de paradas por mantenimiento realizadas en un sistema, obteniendo un mayor rendimiento, reduciendo los mantenimientos correctivos y realizando mantenimientos preventivos con la información que proporciona un enfoque predictivo.

Se basa en datos adquiridos durante el proceso para la planificación de un mantenimiento futuro basándose en el estado de salud del sistema y la evolución temporal que se observa en cada instante, lo que aporta un valor diferente conforme se acumulan medidas nuevas. En el mantenimiento preventivo en cambio, desde un comienzo se establece un tiempo para reemplazar los componentes. Para la planificación de las paradas asociadas al mantenimiento se realizan tres pasos principales, los cuales se muestran en la Figura 2.1:

A- Adquisición de datos.

B- Preprocesado de datos.

C- Sistema de toma de decisiones.

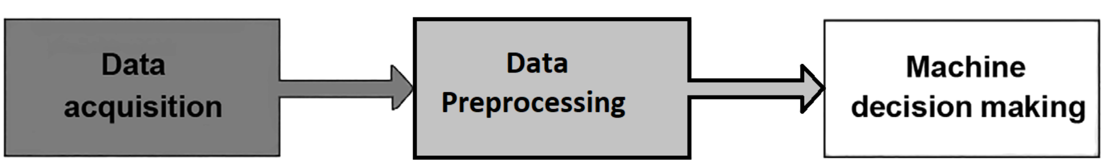


Figura 2.1: Pasos para el mantenimiento predictivo (Galar and Kumar, 2017).

A- Adquisición de datos. Para determinar el estado de salud del sistema y predecir su evolución, se requiere de la adquisición de varias señales asociadas al proceso. Este proceso se resume en la colecta y almacenamiento de datos asociados a múltiples componentes y dependen altamente del proceso. Los datos recolectados se pueden categorizar en dos tipos: datos de eventos y datos de condición. Los datos de eventos son aquellos que muestran algún comportamiento anómalo del componente y las acciones realizadas tras detectar el mismo. Los datos de condición son medidas relacionadas al estado de salud del componente como pueden ser vibraciones, niveles de aceite, presiones, humedad y un largo etcétera.

B- Preprocesado de datos. Los datos adquiridos por equipos de adquisición son susceptibles de tener valores perdidos, valores no consistentes, valores ruidosos etcétera. La detección de esos errores permite la eliminación de información que puede perjudicar la eficacia de un sistema de toma de decisiones. El objetivo siempre es aumentar la calidad de los datos. Esta terminología se refiere a lo fieles que son los datos a la hora de caracterizar el problema que se esté estudiando (Bandemer, 2005). En (Press, 2016; RapidMiner, 2018) se muestra que el preprocesado de datos es uno de los puntos más laboriosos a la hora de crear un sistema de mantenimiento predictivo nuevo (ver Figura 2.2).

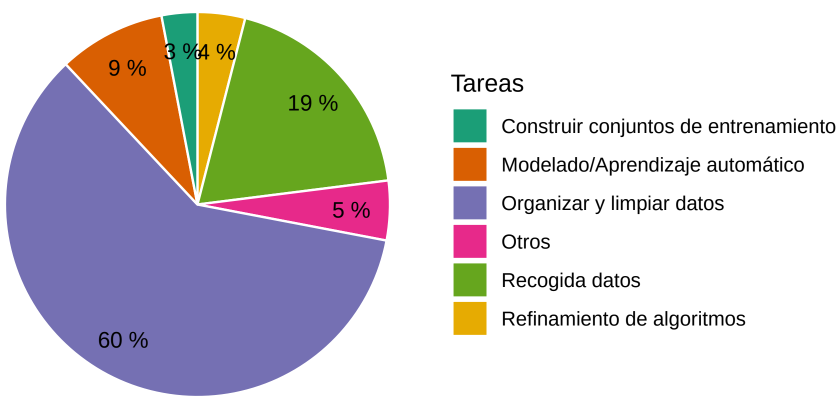


Figura 2.2: Distribución del tiempo que dedica a las diferentes tareas el/la científico/a de datos.

Los métodos de preprocesado de datos se pueden clasificar en las categorías de limpieza de datos, integración de datos, transformación de datos y reducción de datos. Estas categorías se explican a continuación.

Los datos sin procesar generalmente son incompletos, ruidosos o inconsistentes, especialmente los datos de eventos, que se introducen manualmente. Las fuentes de error en los datos son abundantes, además el factor humano uno de los factores más relevantes son los falles en sensórica.

Los datos con ruido suelen causar confusión en el procedimiento de predicción y, en general, no existe una forma simple de limpiarlos. Hay que tener en cuenta la gran dependencia que tendrán los métodos de limpieza en función de los datos y el proceso en estudio. Algunas técnicas se basan en la inspección visual, apoyada en gran parte por alguna herramienta gráfica. Los valores medios y las medianas se usan habitualmente para rellenar valores desconocidos o perdidos. Se pueden utilizar métodos más sofisticados como las técnicas de regresión para estimar los valores perdidos. En (Wei et al., 2018) se compararon ocho métodos diferentes para recuperar datos ausentes para datos de metabólica basados en espectrometría de masas. La detección y eliminación de datos erróneos y con ruido mejora la calidad de los mismos (Lenzerini, 2002). El trabajo presentado en (Libralon et al., 2009) propuso el uso de métodos de agrupamiento para la detección de ruido.

Los valores atípicos de datos también se pueden detectar mediante técnicas de agrupación, donde los valores similares se organizan en grupos. Los valores que se establecen fuera de los *clusters* se considerarán valores atípicos. En (Jin et al., 2019) se aplicó un método de clasificación de una sola clase para detectar puntos de cambio en datos de series temporales para la detección de degradaciones del sistema. En (Maronna et al., 2006) se propuso otro método llamado regla de edición de tres sigmas basado en la distancia de cada punto respecto a un valor medio. Esta metodología ha sido utilizada en (Jimenez Cortadi et al., 2018) para la detección de valores atípicos en un proceso de torneado radial.

La integración de datos es el proceso de combinar, limpiar y presentar datos de forma unificada. Esto incluye reunir datos de una amplia variedad de sistemas de distinto origen, eliminar duplicados, limpiar datos basados en reglas comerciales y transformarlos en el formato requerido. El término también cubre varias áreas en la gestión de big data, como la migración de datos, la integración de aplicaciones y la gestión de datos.

La transformación de datos se basa en la alteración del formato en otro distinto. El principal objetivo es la simplificación y mejora del modelo. Algunas transformaciones pueden acarrear una mejora en la calidad de los datos. Esta mejora suele darse al eliminar el ruido en aquellos datos generados por el sistema cuando se tiene una adquisición inadecuada. En (Mills, 2019) se puede encontrar un resumen de varias técnicas relacionadas con el suavizado. Entre ellas se encuentran los regresores y los agrupamientos. Yahyaoui and Al-Daihani (2019) sugirió un nuevo modelo de Agregación simbólica aproximada (SAX) y comparó los resultados obtenidos por ese modelo con varios estándares, obteniendo mejores resultados en la clasificación de series temporales.

Las técnicas de reducción de dimensionalidad están fuertemente vinculadas a los métodos de visualización. En casos de dimensionalidad alta, la reducción y reinterpretación de las variables ha sido competencia de la comunidad estadística y matemática durante muchos años. Dentro de esta reducción siempre se ha buscado el equilibrio entre tener el menor numero de variables y la mayor cantidad de información. Para ello se han desarrollado multitud de técnicas, entre las cuales se encuentran: análisis de componentes principales (Jolliffe and Cadima, 2016); proyecciones a estructuras latentes (Eriksson et al., 2006); análisis bayesiano (Berry and Berry, 1996); agrupación jerárquica (Johnson, 1967); y técnicas de medición de la similitud como la de Tanimoto (Willett et al., 1986).

C- Sistema de toma de decisiones. Este es el último paso a la hora de determinar un mantenimiento, que puede dividirse en dos categorías principales: diagnosis y prognosis. La diagnosis se centra en la detección, identificación y aislamiento de los fallos cuando se producen, mientras que la prognosis pretende predecir los fallos antes de que se produzcan y está relacionado con el mantenimiento predictivo.

Por ejemplo, el diagnóstico de fallos cumple un papel importante en la búsqueda de la relación entre los datos monitorizados y el estado de salud de las máquinas (Lei, 2016). Tradicionalmente, esta relación era expresada por ingenieros con gran experiencia. En la industria, se busca una manera automática de realizar este tipo de diagnóstico para reducir el tiempo de parada y mejorar la precisión de diagnóstico. En particular, con la ayuda de la inteligencia artificial, se pretende que el procedimiento de diagnóstico de fallos sea lo suficientemente inteligente como para detectar y reconocer automáticamente el estado de salud de las máquinas (Hoang and Kang, 2019; Dai and Gao, 2013).

Para la obtención de diagnósticos de fallo inteligentes (IFD) se utilizan técnicas de aprendizaje automático como las redes neuronales artificiales (ANN), máquinas de vectores soporte (SVM) y redes neuronales profundas (DNN). El diagnostico en general se realiza de manera supervisada, esto es, se determina que el sistema se encuentra en un estado determinado que ya ha sucedido previamente y del cual tenemos información.

Por otra parte, la prognosis es hoy en día un pilar fundamental de investigación, de interés para todas las empresas debido al gran valor que aporta. Consiste en la predicción precoz de fallos basándose en los datos históricos recogidos y la tendencia que muestran estos en función del tiempo. Este tipo de fallos generalmente vienen asociados a un fin de vida inadecuado por parte del sistema en estudio (Galar and Kumar, 2017) y la estimación del mismo se realiza mediante el cálculo de la vida útil remanente (RUL). La estimación de RUL generalmente se trata de una forma no supervisada debido a que generalmente el fallo en estudio suele acarrear un gran coste económico y no se realizan mediciones hasta fin de vida del sistema. Los modelos que encontramos por tanto para este tipo de cálculos son más complejos y a menudo se requiere de gran conocimiento teórico del problema para establecer criterios de alertas y mantenimientos en los sistemas.

Aunque pueda parecer contradictorio, la diagnosis y la prognosis son muchas veces complementarios en el sentido de que el diagnóstico añade nueva información del proceso. Esto permite pasar de un problema no supervisado a uno supervisado; y en general, un modelo supervisado es más fácil de desarrollar y tiene mayor precisión a la hora de predecir futuros estados del sistema, lo que implica un mejor modelo de pronóstico.

2.2. Estrategias para diagnosis y prognosis

Los sistemas de toma de decisiones son la parte final del proceso de la estrategia de mantenimiento predictivo y es donde nos vamos a centrar más en este proyecto de tesis. Existe una gran variedad de métodos con capacidad para establecer criterios de mantenimiento. Estos se dividen en 4 clases en función de la información utilizada para el cálculo del mismo: sistemas basados en la experiencia, sistemas basados en datos, sistemas basados en la física del proceso y sistemas híbridos. A continuación se exponen varios de esos modelos.

2.2.1. Basados en experiencia

Los sistemas basados en la experiencia se centran en la elección de mantenimientos en función del conocimiento táctico del empleado. Basado en antecedentes vividos en el sistema, se realizan una serie de acciones que proveen al mismo de una mayor vida. Estas estrategias de mantenimiento no requieren de una alta capacidad computacional aunque si de un conocimiento del proceso muy alto.

2.2.1.1. Sistemas basados en reglas

Los sistemas basados en reglas son sistemas simples capaces de diagnosticar fallos muy conocidos. Estos sistemas permiten de manera sencilla y con un coste computacional muy bajo la clasificación de datos mediante lógica clásica.

Una regla en este contexto es una proposición lógica que relaciona dos o más objetos del dominio e incluye dos partes, la condición y la conclusión, que se suelen basar en umbrales que sobrepasan alguna de las características extraídas de los datos. Cada una de estas partes es una expresión lógica con una o más afirmaciones las cuales vienen enlazadas por operadores lógicos.

En cuanto a las aplicaciones en el mundo de la diagnosis, se realiza en un amplio abanico de sectores, desde medicina hasta maquinaria pesada. En (Guo et al., 2019) se presenta una aplicación de los sistemas basados en reglas para el diagnostico de 9 modos de fallo aplicados en un flujo de aire. Los resultados mostraron la capacidad de diagnosticar correctamente el 85.13 % de los fallos. El trabajo realizado en (Sanz et al., 2014) presenta un diagnóstico para problemas cardiovasculares mediante sistemas basados en reglas. Los resultados mostraron una mejora respecto a métodos clásicos aplicados en el mismo ámbito. En el mundo de la maquinaria rotativa (Ding and Wach, 1994) implementa el conocimiento experto para la realización de un sistema basado en reglas.

2.2.1.2. Lógica difusa

La lógica difusa es una disciplina matemática presentada a mediados de los setenta (Zadeh, 1978) introducido junto con el concepto de conjunto difuso. La lógica difusa permite representar el conocimiento común, mayoritariamente lingüístico e impreciso en un lenguaje matemático a través de conjuntos difusos y funciones asociadas a ellos.

A diferencia de la lógica clásica, en la cual el diagnóstico de una determinada instancia i es cierta o falsa (**en binario** 1 o 0) , en lógica difusa se define esa frontera entre cierto y falso de manera menos drástica dando un grado de certeza y falsedad a cada instancia (**rango** de 0 a 1). Visto desde esta perspectiva, se podría considerar la lógica clásica como un caso particular extremo de la lógica difusa. La diferencia entre ambas lógicas se aprecia en la Figura 2.3 en la que se muestra la función característica sigmoidal. Existen una gran variedad de ellas y las más utilizadas se pueden encontrar en (Jang et al., 1997)

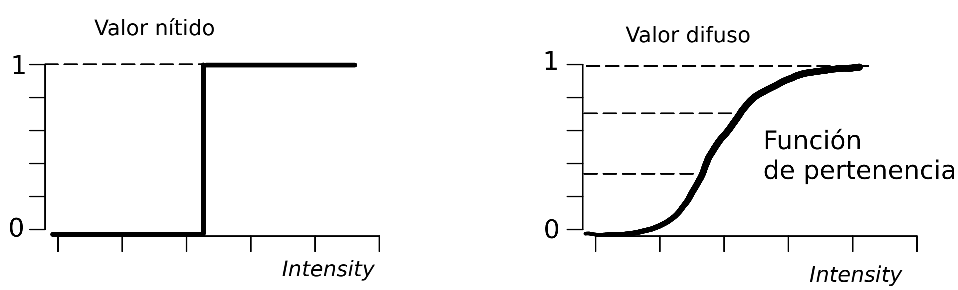


Figura 2.3: Lógica clásica vs lógica difusa Sleit et al..

En cuanto a su aplicación en diagnostico y pronostico de datos, nos encontramos con múltiples artículos relacionados con ello. En (Hou and Huang, 2004) se presenta un método de diagnóstico basado en lógica difusa aplicado al sector de fabricación. Los resultados muestran mejores resultados en datos ruidosos que los modelos estándar. El estudio desarrollado por Arji et al. (2019) expone un diagnóstico y clasificación de datos relacionados con una enfermedad y muestra la gran capacidad de estos modelos para un diagnóstico adecuado. Mammar et al. (2019) presenta una aplicación novedosa de la lógica difusa para el diagnóstico del estado de hidratación en un combustible en desarrollo. En el trabajo realizado en (Rocha, 2020) se realiza el diagnóstico y la detección de fallos con el objetivo de reducir el número de falsos positivos que se generan en un motor.

2.2.2. Sistemas basados en datos

Los sistemas basados en datos son algoritmos matemáticos cuyas decisiones de mantenimiento se centran en los datos recogidos por una serie de sensores ubicados en el sistema. Estos algoritmos requieren de un gran número de valores con los que entrenar para la obtención de tendencias y patrones que caractericen el sistema.

2.2.2.1. Redes Neuronales Artificiales (*ANN*)

Las redes neuronales son un conjunto de algoritmos, basados en la forma de trabajar del cerebro humano. Consisten en un grupo de unidades de procesamiento simple, denominadas neurona, conectadas entre sí, que procesan información mediante conexiones entre las neuronas denominas enlaces (véase Figura. 2.4). Desde el punto de vista matemático, es un complejo problema de optimización donde hay que encontrar los enlaces de las conexiones que minimizan la función de error de ajuste establecido. Es decir, los enlaces se modifican durante el período de optimización o aprendizaje y permiten obtener una mejor clasificación de los distintos modos de fallo en estudio. Aunque en sus inicios únicamente se trabajaba en clasificación, hoy en día las redes neuronales han evolucionado mucho y son capaces de realizar predicciones. Las redes neuronales trabajan exclusivamente con valores numéricos, contenidos en vectores, es por ello que deben adaptarse a las diferentes entradas del mundo real, ya sean imágenes, sonido, texto o series temporales.

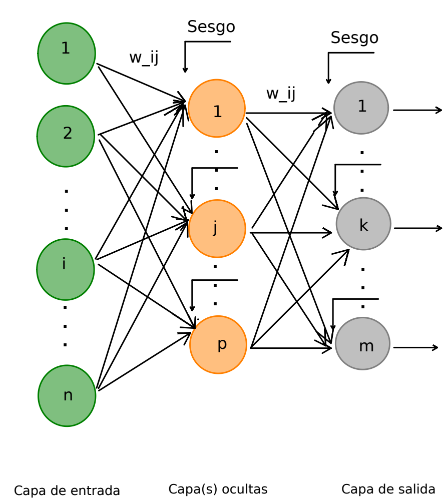


Figura 2.4: Estructura de una red neuronal (Moghaddam et al., 2016).

Las redes neuronales permiten clasificar conjuntos de datos no etiquetados basándose en la clasificación aprendida mediante un histórico de datos etiquetado (aprendizaje supervisado) con el que previamente se ha entrenado. En el ámbito del diagnóstico de fallos se traduce en la capacidad de identificar un modo de fallo concreto para unos datos nuevos, siempre y cuando en los datos de entrenamiento esté contemplado ese fallo. En el estudio de series temporales, también permite el pronóstico de datos basándose en la evolución de los datos actuales y el histórico de los mismos.

Una red neuronal consta de múltiples capas de neuronas unidas entre sí. La capa inicial se denomina capa de entrada y contiene n neuronas, viene determinado por el número de variables/características que se recogen del sistema (variables independientes del sistema). Las capas ocultas se componen de un numero p de neuronas y es la única capa que puede aparecer más de una vez. Tras las capas ocultas se encuentra la capa de salida que tiene m neuronas, definidas por el numero de modos de fallo asociados y las características o mediciones asociados a los mismos. Las conexiones entre las diferentes capas (i, j) de neuronas vienen asociadas un peso w_{ij}, el cual se ajusta durante el entrenamiento de la red para la obtención de un modelo óptimo.

Partiendo de esta idea general, hay diferentes arquitecturas para las redes neuronales. Se denomina arquitectura a la topología, estructura o patrón de conexiones de una red neuronal. En una red neuronal artificial los nodos (neuronas) se conectan entre sí de manera direccional, es decir, la información solamente puede propagarse en un único sentido. Teniendo en cuenta el flujo de datos, podemos distinguir entre redes unidireccionales (perceptron) y redes recurrentes o realimentadas. Mientras que en las redes unidireccionales la información circula en un único sentido, ya sea hacia adelante o hacia atrás, en las redes recurrentes o realimentadas la información puede circular entre las distintas capas de neuronas en cualquier sentido, incluso en el de salida-entrada.

Estos algoritmos han sido usados en múltiples ocasiones para la clasificación y el diagnóstico de fallos. Por ejemplo, Xu et al. (2020) se utilizan redes neuronales para la detección de fallos en equipos rotativos industriales. En el estudio realizado por Yan and Ma (2004) se desarrolla un sistema de diagnóstico de fallos para un motor diésel de combustión basándose en este paradigma. Los resultados obtenidos aportan una gran precisión. En (Zhou et al., 2020a) se presenta una nueva metodología basada en las redes neuronales para la detección de modos de fallo aplicada a maquinaria rotativa. En datos no balanceados, la metodología expuesta presenta mejoras sustanciales respecto a las técnicas tradicionales aplicadas en este campo. Zhou et al. (2020b) presentan una red neuronal convolucional robusta y capaz de realizar un diagnóstico en tiempo real para turbinas de gas. En el trabajo (Chen et al., 2020) se ha realizado un diagnóstico de fallos en rodamientos mediante redes neuronales convolucionales.

2.2.2.2. Máquinas de vectores soporte (*SVM*)

Las maquinas de vectores soporte (SVM) permiten clasificar conjuntos de datos no etiquetados. Para ello se construye una hipersuperficie a partir de las características de los datos durante el entrenamiento, y esta construcción se realiza con datos supervisados. Esta hipersuperficie permite etiquetar los datos nuevos dentro de las categorías aprendidas, que en el tema de diagnóstico de fallos se referirá a los fallos considerados.

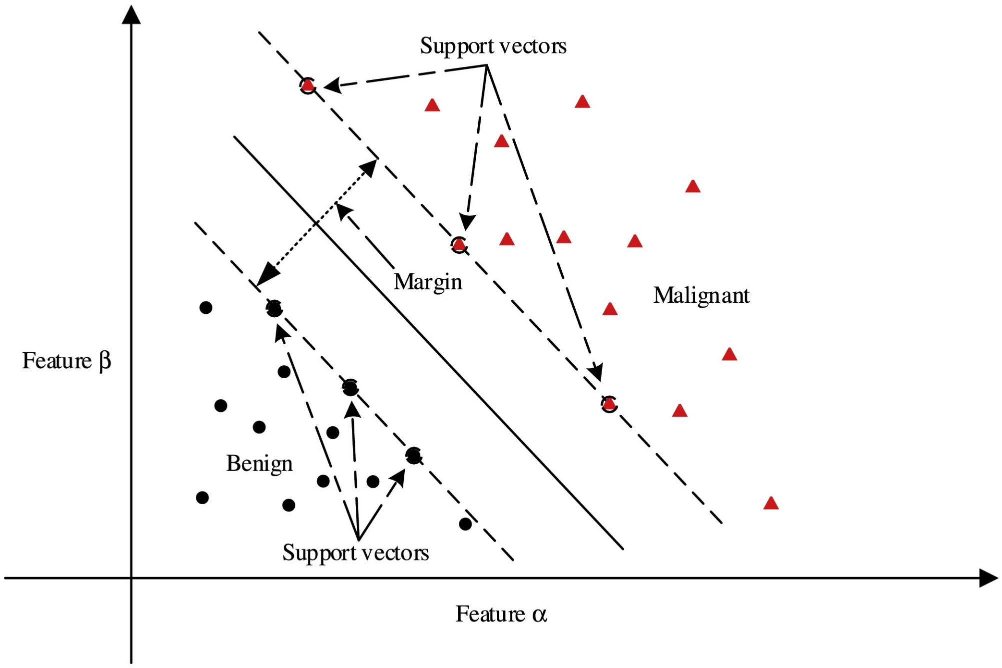


Figura 2.5: Imagen ilustrativa del funcionamiento de *SVM* para el caso lineal (Wang et al., 2018).

Las máquinas de vectores soporte son algoritmos de clasificación basados en la creación de hiperplanos o hipersuperficies capaces de distinguir entre dos clases. Es capaz de establecer un umbral maximizando la distancia mínima entre las clases, denominado como margen, (véase Figura 2.5) de tal modo que, al recibir un nuevo dato no etiquetado, es capaz de asignarle una clase en función de la ubicación del mismo en el hiperespacio asociado (cuyas dimensiones son las n características asociadas al mismo). Para casos donde el hiperplano necesario no es una línea recta como la de la Figura 2.5, nos encontramos la necesidad de realizar una hipersuperficie curvada (véase Figura 2.6). Para la obtención de esa superficie la solución consiste en la aplicación de un kernel (transformación del espacio) que nos permita esa separación.

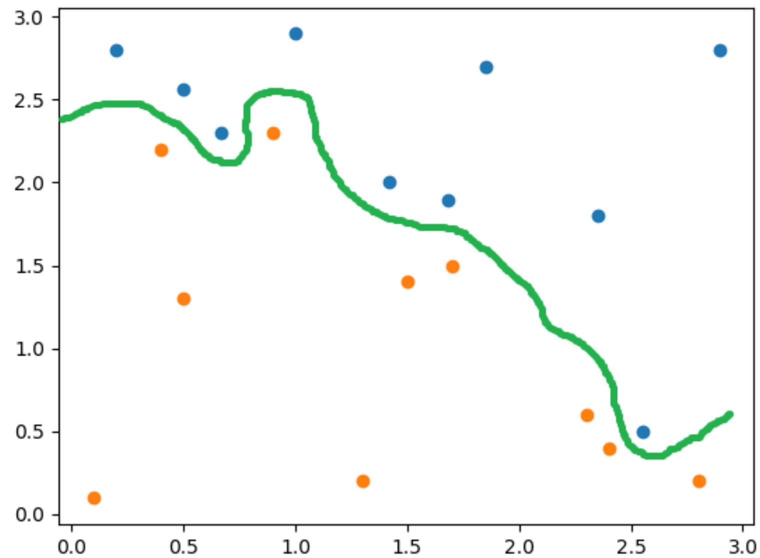


Figura 2.6: Imagen de un ejemplo de separación de las clases por un *SVM* no lineal.

Las *SVM* han sido y son ampliamente utilizadas en el ámbito de la clasificación de modos de fallo. En (Hu et al., 2007) se presenta un método basado en *SVM* para la detección de fallos en rodamientos. Los resultados demuestran la capacidad del modelo *SVM* para identificar la severidad de los fallos. Lihui et al. (2018) realizan un diagnóstico de fallos aplicado en una caja de cambios. Los resultados, aplicados en datos de laboratorio, muestran una gran capacidad de diagnóstico. El estudio realizado por ALTobi et al. (2019) presenta una comparación de varias técnicas para el diagnóstico de fallos en una bomba centrífuga entre los cuales se encuentra el modelo *SVM*. Los resultados muestran una capacidad mayor por parte de *SVM* utilizando un menor número de características. En (Yan and Jia, 2018) se propone una nueva metodología basada en *SVM* para la detección e identificación de múltiples modos de fallo en rodamientos. Los resultados obtienen gran exactitud para diferentes condiciones de trabajo.

2.2.2.3. Técnicas de agrupamiento

Las técnicas de agrupamiento o clustering son técnicas no supervisadas que se encargan de agrupar datos en función de su similitud. En el ámbito de la diagnosis, las técnicas de clustering permiten detectar el estado de salud en el que se encuentra un sistema en un determinado instante basándose en un histórico de datos con el que se ha entrenado previamente. La clasificación de un dato se establece por la pertenencia de este a una agrupación concreta.

El funcionamiento de estas técnicas se basa en la agrupación de los datos adquiridos en función de la similitud que tienen los mismos entre sí. Se extraen unas características de los datos recogidos y se establece un criterio de proximidad (distancia entre los valores). Se realiza el cálculo de ese criterio de proximidad mediante la distancia que separa cada pareja de datos adquiridos y finalmente se realizan las agrupaciones en un número de grupos que viene determinado en función de la técnica y del proceso en estudio. En la Figura 2.7 se aprecia una agrupación para unos datos bidimensionales.

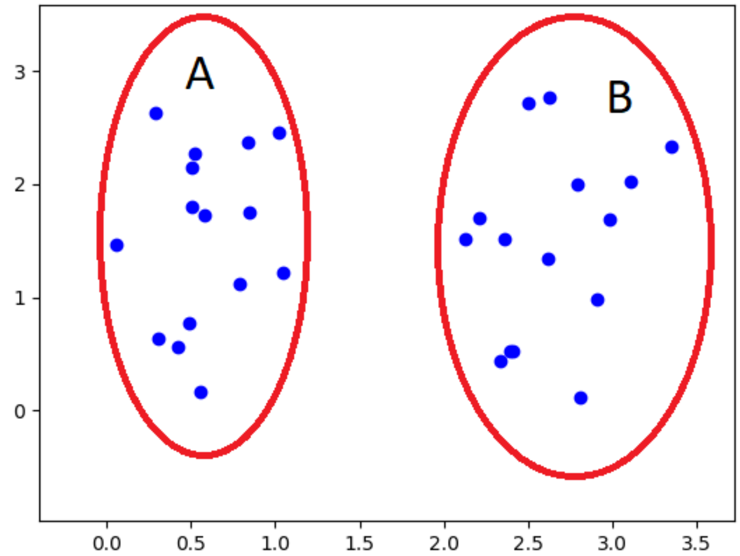


Figura 2.7: Agrupamiento de señales en 2 dimensiones (Saxena et al., 2017).

Las técnicas de clustering son utilizadas frecuentemente a día de hoy en el ámbito del mantenimiento sobre todo para la parte de la diagnosis. En (Li et al., 2020) se presenta un diagnóstico de fallo para unos datos reales asociados a maquinaria rotativa. Los resultados obtenidos son prometedores en la exploración de estos fallos para datos no supervisados. El trabajo mostrado por Lu and Li (2020) expone un método de diagnóstico de fallos para circuitos de frenos mediante técnicas de agrupamiento. El coeficiente de similitud es obtenido basándose en los datos supervisados de entrenamiento. Los resultados muestran la capacidad de detectar fallos no contemplados dentro de los datos de entrenamiento. Li et al. (2020) realizaron un estudio para la diagnosis de fallos en rodamientos de bolas mediante técnicas de agrupamiento basadas en densidades. El estudio realizado en (Rodríguez-Ramos et al., 2018) propone una aproximación para diagnóstico de fallos en línea basándose en técnicas de clustering y lógica difusa. Esta aproximación incorpora un mecanismo de aprendizaje automático que le ha permitido obtener unos excelentes resultados.

2.2.2.4. Regresión polinómica (*PR*)

Una regresión polinómica se basa en la aproximación de una variable dependiente y mediante un polinomio de orden p de las variables independientes del sistema (véase 2.1 en el caso de una única variable independiente x). De entre todas las posibles curvas que aproximan los datos recogidos la elección de la curva idónea se basa en encontrar aquellos pesos w_k ($k = 0, \ldots, p$) o coeficientes que ofrecen la curva que mejor se aproxima a la real. Esa aproximación entre la curva polinómica y la real se establece habitualmente con el método de mínimos cuadrados o el gradiente descendente.

$$y = w_0 + w_1 \cdot x + w_2 \cdot x^2 + \ldots + w_p \cdot x^p \ + \ e\,, \tag{2.1}$$

donde e es el error aleatorio o residuo.

Las regresiones polinómicas aunque parezcan sencillas tienen una gran aplicación a casos reales en la industria. (Zhang and Li, 2018) realizaron una aplicación en la industria de los semiconductores para la detección de fallos, cuyo resultado mejora la aplicación de un modelo clásico en la materia. El trabajo realizado en (Karamavuş and Özkan, 2019) compara varios regresores para la obtención del nivel ictericia de la piel. Para esta predicción se utiliza la regresión polinómica múltiple (MPR), la red neuronal artificial (RNA) y la regresión de vector de soporte (SVR). El estudio de Kumar et al. (2019) utiliza una (MPR) para la predicción de RUL en un banco de pruebas de mecanizado CNC equipado con sensores de fuerza de empuje y de torsión para la supervisión de las brocas. En (Cica et al., 2020) también se realiza una comparación de distintos regresores aplicados a predecir la fuerza del mecanizado, presión y potencia de corte. Los métodos comparados son la regresión polinómica (PR), la regresión del vector de soporte y la regresión del proceso gaussiano (GPR).

2.2.2.5. Modelos Ocultos de Markov (HMM)

La cadena de Markov, es un concepto desarrollado dentro de la teoría de la probabilidad y la estadística que establece una fuerte dependencia entre un evento y un estado anterior. Este tipo de algoritmo sirve para sistemas repetitivos irreversibles y de larga duración, donde la evolución en los estados de la cadena permite establecer una distancia hasta el evento en estudio.

En un modelo de Markov, se asume que el sistema se encuentra siempre dentro de uno de los finitos estados conocidos, los cuales son todos posibles y mutuamente excluyentes (no se puede estar en más de un estado a la vez). Los eventos que suceden en el sistema se modelizan como transiciones de unos estados a otros que se producen en períodos uniformes de tiempo (denominados ciclos de Markov) y con una probabilidad de transición que depende del estado en el que se encuentre el sistema. Teniendo en cuenta el ámbito del mantenimiento industrial que tratamos en este proyecto de tesis, en cada instante las cadenas de Markov nos proporcionarán una probabilidad de alcanzar un estado determinado asociado a un fallo conocido.

En cuanto a la aplicación en la literatura de estos modelos, se pueden encontrar multitud de trabajos relacionados. (Li et al., 2018) realizaron una detección de fallos en un rodamiento y se demuestra su superioridad respecto a métodos convencionales. El estudio presentado en (Li et al., 2019) nos presenta una aplicación en un rodamiento de un aerogenerador obteniendo un método de fiabilidad del mismo. El trabajo realizado por Arpaia et al. (2020) también genera un modelo de detección de fallos aplicando los modelos de Markov basándose en los datos adquiridos de los fluidos de la maquinaria asociada al proceso.

2.2.2.6. ARIMA

Lo modelos $ARIMA$ son modelos estadísticos que utilizan variaciones y regresiones de datos para la detección de patrones y para la predicción de valores futuros a lo largo del tiempo. Se trata de un modelo dinámico de series temporales, es decir, las estimaciones futuras vienen explicadas por los datos recogidos previamente. Para la prognosis permite la predicción de valores futuros basándose en los últimos datos disponibles de manera adaptativa, lo que le da un gran potencial en aquellos sistemas de pequeño margen de error como las predicciones bursátiles y el desgaste de herramientas en procesos mecánicos rápidos.

El modelo $ARIMA$ es la combinación de los modelos autorregresivos (AR) y modelos de medias móviles (MA). Un modelo autorregresivo describe un proceso en el que los datos en un momento dado son predecibles a partir de los datos previos del proceso más un termino de error. En estos modelos, se establece un parámetro p que nos identifica el número de datos previos a tener en cuenta para la realización del modelo. Un modelo de medias móviles permite el calculo del dato actual mediante la componente aleatoria del dato actual y, en menor medida, de los q valores aleatorios previos. Un modelo $ARIMA$ es la fusión de los modelos comentados previamente al cual se le ha aplicado un número de integraciones d que permite predecir una serie de datos futuros.

El modelo $ARIMA$ ha cogido gran importancia recientemente en relación a la predicción de series temporales. En el artículo (Yuan et al., 2016) se expone una metodología basada en estos modelos para la predicción de consumo energético en China y compara los resultados obtenidos entre $ARIMA$ y un modelo clásico en este ámbito. (Contreras et al., 2003) proponen una predicción del precio de la electricidad mediante el uso de la serie temporal del mismo. Los artículos (Laayouj and Jamouli, 2015; Saha et al., 2009) realizan un cálculo de vida útil remanente en baterías de Ion-Litio con el objetivo de predecir su degradación a lo largo del tiempo. Incluso hoy en día se aplica esta técnica para la predicción de tendencias en enfermedades como se realiza en el trabajo (Benvenuto et al., 2020) con el COVID-19.

2.2.2.7. Procesos Gaussianos Regresivos (GPR)

Un proceso Gaussiano es una colección de variables aleatorias, que cumplen que cualquier subconjunto finito de la colección, tiene una distribución Gaussiana. Se puede asemejar a una distribución Gaussiana multivariante de dimensiones infinitas. Dentro de esta distribución Gaussiana, se puede incorporar el conocimiento previo sobre el espacio de funciones a través de la selección de las funciones media y de covarianza.

La forma de la función media y la función del kernel de covarianza en la distribución Gaussiana es elegida y ajustada durante la selección del modelo. La función media es típicamente constante, ya sea cero o la media del conjunto de datos de entrenamiento. Hay muchas opciones para la función del kernel de covarianza: puede tener muchas formas siempre que siga las propiedades de un kernel. Algunas funciones comunes del kernel son la constante, la lineal, la exponencial cuadrada y la función de base radial (RBF).

A la hora de ajustar los hiperparámetros de la función del kernel de covarianza se suele utilizar una maximización de la probabilidad marginal logarítmica de los datos.

Para la predicción de la distribución posterior, los datos y la observación de prueba están condicionados y debido a la distribución Gaussiana mencionada, la distribución normal resultante puede ser completamente descrita por la media y la covarianza.

En el sector industrial los GPR tienen su importancia y aparecen junto a múltiples aplicaciones. (Lu et al., 2020) han generado un modelo de predicción de la rugosidad de la superficie para el hierro fundido de grafito compactado mediante GPR. Los resultados muestran que la velocidad de corte afecta significativamente a la rugosidad de la superficie. El trabajo realizado por Hassani et al. (2019) presenta una aplicación del método GPR para predecir el RUL de un giroscopio. Los resultados muestran que empleando el método GPR, el pronóstico para el rodamiento de bolas puede predecir con éxito el defecto antes de que ocurra y predice de manera adecuada el RUL del sistema en estudio. En (Aye and Heyns, 2017) se expone una aplicación del método GPR para la predicción de RUL de los cojinetes de baja velocidad basándose en señales de emisión acústica. Los resultados muestran errores muy bajos para rodamientos a baja velocidad.

2.2.2.8. Métodos de supervivencia

Los métodos y análisis de supervivencia se enmarca en estudios en los que el objetivo es estudiar los tiempos hasta que ocurre un evento de interés. Es decir, fijado el evento de interés, se observan los tiempos hasta que ocurre el evento, lo que en mantenimiento se conoce como tiempo a fallo (TTF), y el estudio se centra en la modelización de estos tiempos. Una característica de estos estudios es la aparición de datos censurados. Esto ocurre cuanto no se observa el tiempo hasta el evento, sino que se observa, por ejemplo, un tiempo anterior al evento. Este tipo de análisis tiene por objetivo la modelización de la función de supervivencia y la función de riesgo del evento.

Entre los modelos de supervivencia, la regresión semiparamétrica de *Cox* es una de las más populares. Esta técnica integra los tiempos de supervivencia observados junto con la información de censura, con covariables relevantes para el evento. El modelo clásico de regresión *Cox* establece los riesgos proporcionales en el tiempo y considera las covariables estáticas, consideración que limita su uso a situaciones en las que esas covariables no varían o esa variación no es relevante. La aparición de modelos conjuntos de datos longitudinales y de supervivencia viene a cubrir la necesidad de poder integrar covariables dependientes del tiempo en el modelo de *Cox*.

El uso de estas técnicas está muy extendido en el ámbito biomédico en relación a la supervivencia de un paciente o aparición de eventos en el desarrollo de enfermedades. Sin embargo, en el ámbito del mantenimiento estas metodologías han adquirido gran relevancia más recientemente al considerar que un sistema podría ser tratado como un paciente en el sector industrial. Esto es, se considera que el sistema tiene una vida inicial estimada que puede alargarse realizando una serie de mantenimientos/modificaciones en sus hábitos para que el desgaste sea menor.

En el estudio (Chen et al., 2020) se presenta un modelo de mantenimiento predictivo mediante el uso del modelo de *Cox*. Los datos utilizados han sido datos reales en los cuales el método propuesto ha mejorado el existente. Equeter et al. (2016) aplican el modelo de supervivencia para la estimación del RUL en un sistema de torneado. El trabajo mostrado por Verhagen and De Boer (2018) expone una solución para el mantenimiento predictivo en aeronaves mediante el uso de métodos de supervivencia. Los resultados muestran la posibilidad de reducir el número de mantenimientos imprevistos aplicando esta metodología.

2.2.3. Sistemas basados en la física del proceso

Los sistemas basados en la física son aquellos en los que se tiene un gran conocimiento del proceso y las ecuaciones que rigen el mismo son conocidas. Esto es, se conoce el comportamiento del sistema de manera detallada y analíticamente viene determinado por una serie de ecuaciones.

2.2.3.1. Método de filtrado de partículas (*PF*)

El filtro de partículas se emplea para la estimación del estado de un sistema que cambia a lo largo del tiempo. Se trata de un filtro en el que la densidad se representa mediante una distribución de partículas en el espacio de estados. Este enfoque se ha desarrollado de forma independiente en los últimos años en campos como la estadística, la economía o la visión artificial.

El filtrado de partículas asume que somos capaces de simular N muestras independientes y aleatorias de idéntica distribución que se denominan partículas según una distribución de probabilidad (véase Andrieu et al. (2001)). A estas partículas, se les aplica un modelo de movimiento, lo que genera un nuevo conjunto de muestras. Estas muestras representan la predicción de la variable de estado, sin considerar la observación. En función de la proximidad de esta predicción con el estado real, se otorga un peso p_i a cada muestra i. Finalmente se remuestrea el conjunto de muestras, extrayendo (con reemplazo) N muestras del conjunto actual, con probabilidad proporcional al peso de cada una. La estimación final del estado se hará con una media de las trayectorias ponderada por los pesos.

La aplicación de filtrados de partículas es cada día mayor en el ámbito de la prognosis. György et al. (2014) presentan una aplicación de PF en un sistema no lineal teórico, donde se introducen diferentes no linealidades en el modelo de observación y compara los resultados con otros modelos similares. El trabajo realizado por Fan et al. (2015) expone un estudio sobre un modo de fallo común en las fuentes de luz LED que consiste en la degradación del lumen. Se describe un enfoque de pronóstico basado en un filtro de partículas para predecir la vida útil de mantenimiento del lumen de las fuentes de luz LED. Los resultados muestran mejoras respecto a la metodología actual en ese ámbito. En el sector ferroviario, la aplicación de PF está presente en el artículo (Mishra et al., 2017) donde se estudia el desgaste de las vías. Los resultados del pronóstico basado en el filtro de partículas se comparan con los resultados del método de regresión estándar para cuatro cambios de vías férreas, y el método del filtro de partículas muestra un resultado similar o mejor para los cuatro casos. Hu et al. (2015) abordan el problema de la predicción de la Vida Útil Remanente de los componentes para los que se dispone de un modelo matemático que describe la degradación del componente, pero no se conocen los valores de los parámetros del modelo y no se dispone de las observaciones de las trayectorias de degradación en componentes similares. El enfoque propuesto resuelve este problema utilizando una técnica de filtrado de partículas (PF). Se considera una aplicación numérica en lo que respecta a los pronósticos para las baterías de iones de litio y los resultados muestran unos resultados satisfactorios.

2.2.3.2. Filtros de Kalman

El filtro de Kalman es un filtrado adaptativo que permite identificar situaciones ocultas (no medibles) en un sistema dinámico mediante información de situaciones medibles. Esto es, en procesos en los que no se obtiene información de un estado determinado, permite obtener dichos valores utilizando información de otros estados del sistema y el conocimiento sobre el mismo.

El filtro de Kalman es un algoritmo que permite la proyección lineal de un sistema de variables sobre el conjunto de información disponible, según se va disponiendo de nueva información.

La dinámica se resume en dos pasos:

- La estimación las variables de estado utilizando la dinámica del sistema (etapa de predicción).
- La mejora de esa estimación utilizando la información de las variables medidas (etapa de corrección).

Una característica muy atractiva de esta metodología es que tiene carácter recursivo que permite llevarlo a cabo sin necesidad de almacenar la información de los estados en todos los instantes. Una vez que el algoritmo pronostica el nuevo estado en el momento i, añade un término de corrección y el nuevo estado "corregido" sirve como condición inicial en la siguiente etapa, $i+1$. De esta forma, la estimación de las variables de estado utiliza toda la información disponible hasta ese momento y no sólo la información hasta la etapa anterior al momento en el cual se realiza la estimación.

En el trabajo de Rodger (2012) se muestra una aplicación para reducir el riesgo de fallos en el estado de salud en un vehículo mediante una aproximación del filtro de Kalman. Los resultados muestran la reducción en el tiempo para la estimación de nuevos estados en el sistema. En (Xue et al., 2020) se resuelve el problema de la predicción de RUL para unas baterías de Ion-Litio mediante un filtro de Kalman. En el articulo (Emami et al., 2019) se propone la aplicación de un modelo de Kalman para la predicción a a corto plazo del flujo de vehículos fusionando datos de vehículos conectados y datos asociados a dispositivos Bluetooth.

2.2.4. Sistemas híbridos

Los sistemas híbridos son aquellos en los cuales se combinan diferentes modelos. Esta combinación se realiza con el objetivo de acumular los puntos fuertes de cada uno de los métodos aplicados y así los resultados obtenidos tienen una mayor precisión. Los sistemas híbridos requieren de un conocimiento extenso en varios sistemas de toma de decisiones y no siempre es posible contar con ello. Los sistemas híbridos están adquiriendo gran relevancia en la actualidad y sus aplicaciones son diversas, desde predicciones del precio del petroleo hasta fabricación.

Por ejemplo, Zhang et al. (2015) propusieron un nuevo modelo que combina SVM junto con la optimización de los enjambres de partículas (PSO) para pronosticar los precios del petróleo. En el trabajo de Hou et al. (2019) se consideró la periodicidad y variabilidad del flujo de tráfico y las limitaciones de los modelos de predicción únicos para desarrollar un modelo híbrido adaptativo para predecir el flujo de tráfico a corto plazo. En primer lugar, para predecir el flujo de tráfico se utilizó el método $ARIMA$ y una red neuronal ondulatoria no lineal WNN. A continuación, se combinaron los resultados de los dos modelos individuales mediante lógica difusa y el resultado ponderado se consideró como el volumen de tráfico final previsto del modelo híbrido. En el articulo (Anifowose and Abdulraheem, 2011) se estudió la porosidad y la permeabilidad con un modelo híbrido que se basó en la combinación de tres técnicas de Inteligencia Artificial existentes: Redes Neuronales, SVM y Sistema de Lógica Difusa, aplicando las capacidades de aproximación funcional de las Redes Neuronales, la capacidad de la Lógica Difusa para manejar incertidumbres y la escalabilidad y robustez de las Máquinas Vectoriales de Soporte en el manejo de datos pequeños y de alta dimensión a seis conjuntos de datos. El trabajo demuestra los resultados exitosos de la hibridación en uno de los problemas de la vida real que se encuentran en la producción de petróleo y gas. El trabajo de Chen and Wang (2007) se propone una comparación entre tres modelos: modelos ($ARIMA$), modelo de máquinas vectoriales de apoyo (SVM) y un modelo híbrido hecho con ambos. Para determinar el mejor método, se calcula el error cuadrático medio normalizado ($NMSE$) y el error porcentual medio absoluto ($MAPE$) y el modelo híbrido muestra una mayor precisión.

CAPÍTULO 3

Líneas de investigación

En este capítulo se describen las aportaciones realizadas que están incluidas en diferentes líneas de investigación. Estas aportaciones han dado como resultado contribuciones científicas de impacto para algunas de ellas sobre las que se pondrá un mayor énfasis. Además se describen algunas otras que aunque no han resultado en contribuciones relevantes han servido para enriquecer la capacidad investigadora del aspirante además de contribuir a los proyectos de investigación. Las líneas de investigación que aquí se describen tienen como punto de partida uno o varios proyectos de investigación con clientes industriales o financiados por una entidad pública. Las aportaciones y publicaciones que se describen son fruto de esos proyectos.

3.1. Estimación de la vida útil remanente en superaleaciones

Es conocida la gran exigencia requerida en el sector aeronáutico debido a la relevancia económica que tiene, así como la gran importancia en los mecanismos de seguridad en la fabricación de las aeronaves. Por ello cada una de las piezas que lleva la nave debe pasar rigurosos tests en los cuales se mide la calidad de las mismas. Esta calidad viene muy relacionada con el proceso de mecanizado y está a su vez, muy relacionada con el buen estado de las máquinas y herramientas involucradas en el mecanizado de las piezas. En particular, es importante conocer cuál es el desgaste de la herramienta para poder realizar el cambio de la herramamienta antes de su deterioro. El objetivo de esta línea de investigación ha sido el desarrollo de un modelo capaz de predecir el desgaste de la herramienta que realiza el torneado radial de unas superaleaciones de níquel utilizadas en aeronaves.

Las superaleaciones pueden encontrarse en una amplia variedad de estados, obtenidas mediante procesos de calentamiento y enfriamiento térmico. El proceso considerado en este estudio fue el recocido que produce cambios microestructurales que incluyen la recristalización y el crecimiento del grano. La estructura de cristalización de las aleaciones tratadas a altas temperaturas y durante largos períodos de recocido se romperá y los procesos de recristalización posteriores serán diferentes, dependiendo de la rapidez del proceso de calentamiento o enfriamiento. Obsérvese que, si bien el tratamiento térmico puede provocar el crecimiento de los granos, no ocurre lo mismo con la reducción del tamaño de los mismos. Los procesos de recristalización y crecimiento del grano pueden controlarse regulando los tiempos de calentamiento y de enfriamiento.

Aunque sólo las superaleaciones de níquel entran en el caso de estudio (Waspalloy, Inconel 718 y Haynes), la composición química de las superaleaciones difiere ligeramente. Las pruebas se realizaron a una velocidad de corte de 30 m/min, con una profundidad de corte de 2 mm y una velocidad de avance de 0,1 mm/revolución. En cada prueba se eliminó la misma cantidad total de material, con una longitud de corte en espiral (*SCL*) de 727m, dividida en seis o cuatro pasadas dependiendo de la aleación. Se utilizaron insertos estándar de carburo cementado sin recubrimiento (Sandvik CoromantTCMW16T304, grado Sandvik H13A equivalente a ISO S20) con un radio de punta de 0,4 mm.

En la Figura 3.1 se observan los diferentes tamaños de grano de cada una de las superaleaciones utilizadas en este proyecto.

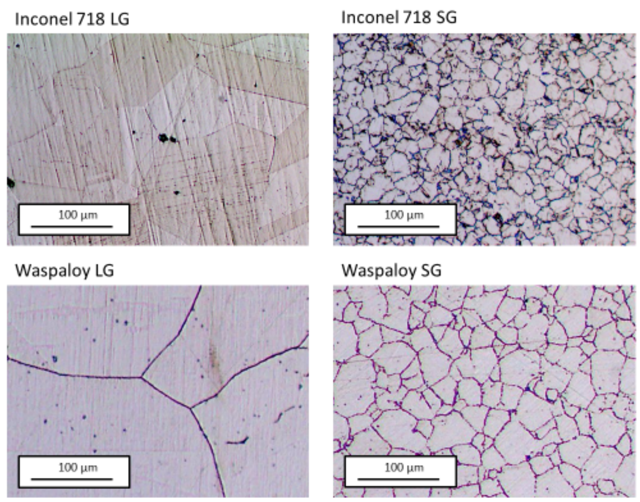


Figura 3.1: Tamaño de grano de las superaleaciones utilizadas en el proyecto.

El proceso de torneado de estos materiales tan duros genera unas temperaturas muy altas y con el objetivo de extender la vida útil de la herramienta suele aplicarse una criogenización a alta presión durante el proceso (véase Figura 3.2).

El trabajo realizado dentro de este proyecto de tesis se ha centrado en conocer cómo evoluciona el desgaste de la herramienta. Así, al terminar cada uno de los mecanizados se midió el desgaste producido en la herramienta de corte. Las herramientas se cambian tras realizar 6 pasadas a una misma pieza. Además, se han recogido los datos relacionados con la fuerza ejercida por la herramienta de corte en el momento del mecanizado en cada uno de los ejes F_x, F_y, F_z.

El primer logro fue la obtención de un modelo de estabilidad aplicado a cada una de las herramientas mediante el estudio de las diferentes pasadas realizadas. Para ello y considerando la primera pasada (con herramienta nueva) como estable, se realizó un análisis de componentes principales considerando la fuerza ejercida por la herramienta. El objetivo de este análisis fue la reducción de la dimensión y visualización de cada una de las pasadas. Una pasada se consideró como inestable si la distancia máxima de alguno de los puntos asociados al mecanizado superaba el doble del valor asociado al primero.

Figura 3.2: Imagen del proceso de criogenización.

El segundo logro obtenido en esta línea fue la modelización del desgaste de la herramienta asociada y la predicción del numero de pasadas posibles a realizar por cada herramienta. Al tener medidas repetidas del desgaste para cada herramienta, se consideró la posible correlación entre los desgastes relativos de una misma herramienta. Para ello se utilizaron modelos mixtos lineales, incluyendo efectos fijos y aleatorios, donde la variable dependiente considerada fue el desgaste de la herramienta y se tuvieron en cuenta las diferentes condiciones iniciales del proceso. Se consideraron efectos aleatorios tanto para el intercepto como para la pendiente en relación a las diferentes pasadas. El estudio de los residuos verificó la bondad del modelo ajustado.

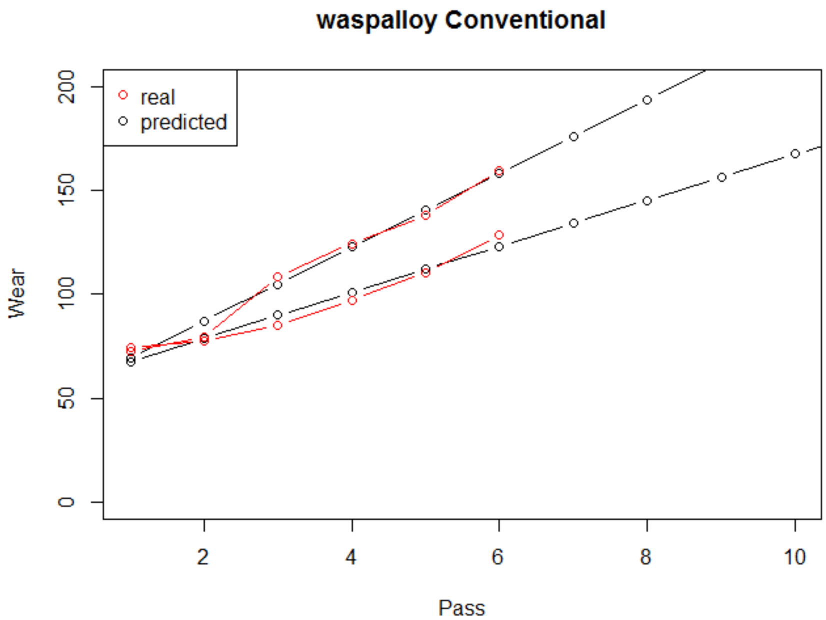
El modelo obtenido muestra las diferencias del desgaste de la herramienta para las diferentes superaleaciones en estudio y en combinación con el método de lubricación utilizado. En la Figura 3.3 se aprecia la tendencia del *Waspalloy* en el cual se presentan en rojo las pasadas realizadas y en negro la predicción de desgaste para las futuras pasadas. Se puede apreciar que el convencional genera un desgaste mucho mayor en la herramienta y que por consiguiente no permite realizar tantas pasadas sin cambio de herramienta como en el caso con lubricación.

El trabajo se realizó como parte del proyecto HIMMOVAL (Número de Acuerdo de Subvención: 620134) dentro del programa CLEAN-SKY, vinculado con el proyecto SAGE2 para el desarrollo de rotor abierto orientado y la entrega de la parte demostradora. La financiación a través de la subvención IT900-16 es también reconocida por el Departamento de Educación, Universidades e Investigación del Gobierno Vasco.

Los logros expuesto en esta línea de investigación permitieron realizar varias publicaciones científicas de alto impacto:

- Alberto Jimenez Cortadi, Itziar Irigoien, Fernando Boto, Basilio Sierra, Alfredo Suarez, Diego Galar, **A statistical data-based approach to instability detection and wear prediction in radial turning processes.** (2018). Eksploatacja i Niezawodność, 20(3), 405-412.

- Alberto Jiménez, Fernando Boto, Itziar Irigoien, Basilio Sierra, and Alfredo Suarez. **Stability analysis of radial turning process for superalloys**. Management Systems in Production Engineering, 25(3):158–162, 2017.



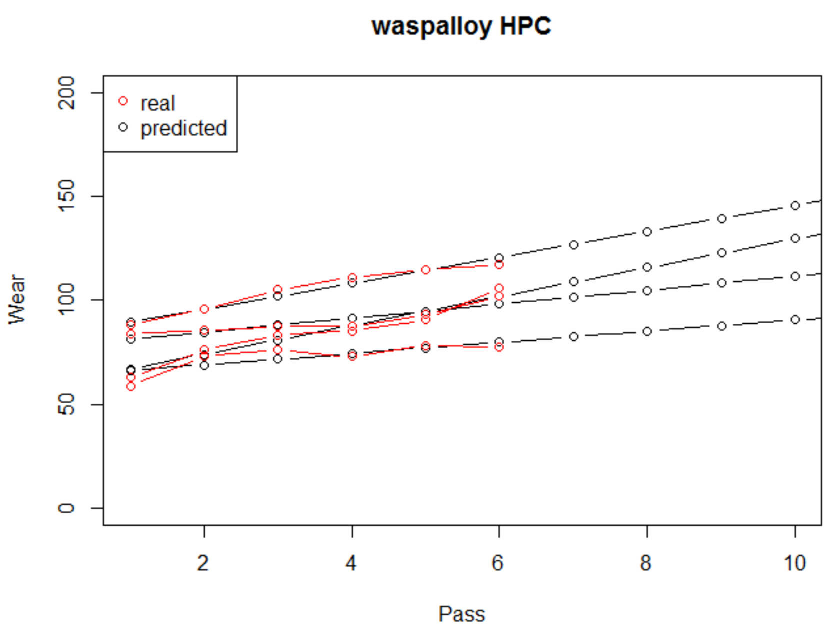


Figura 3.3: Predicción del desgaste de la herramienta para un mismo material y distinta lubricación.

- Alberto Jimenez Cortadi, Fernando Boto, Itziar Irigoien, Basilio Sierra, and Alfredo Suarez. **Instability detection on a radial turning process for superalloys**. In International Joint Conference SOCO2017-CISIS2017-ICEUTE2017 León, Spain, September 6–8, 2017, Proceeding, pages 247–255. Springer, 2017.

3.2. Estimación de *RUL* en máquina herramienta.

Los procesos de mecanizado están viviendo una rápida evolución desde la llegada de la Industria 4.0. La capacidad de obtener información sobre el estado del proceso y cómo va a evolucionar permite planificar mejor las paradas debidas al mantenimiento preventivo y reduce el número de paradas que provocan un mantenimiento correctivo, lo que implica un menor gasto económico. El objetivo de este proyecto fue el desarrollo de un sistema de monitorización en tiempo real y un modelo de predicción de desgaste para un proceso de mecanizado en piezas de pequeño tamaño.

El objetivo de esta línea ha sido investigar en el desarrollo de nuevos y complejos procesos de fabricación (procesos de alto valor) a través de una simulación (el conocimiento), monitorización y análisis de datos, configurando una plataforma de modelización híbrida y actuación flexible (ofreciendo actuación on-line y remota) que permitiera a empresas fabricantes de máquinas y, en especial a sus usuarios, optimizar (en tiempo y coste) drásticamente sus procesos de fabricación.

Los experimentos se llevaron a cabo en un centro de torneado *CNC* con dos postes de herramientas (véase Figura 3.5), que podían moverse en dos ejes independientemente con movimiento longitudinal y transversal. El portaherramientas de corte utilizado fue un C3-MTJNR-22040-16 equipado con un inserto TNMG160408-PF para la superficie externa y un portaherramientas especial equipado con un inserto WNMG060408-PM para el diámetro interno. El torneado realizado se aprecia en la Figura 3.4, siendo azul la parte externa y en rojo la interna. Durante el proceso de mecanizado, las revoluciones de rotación se fijaron en $1800rpm$. La estrategia de mantenimiento que se aplicó en ese momento fue un método muy conservador. El cambio de la herramienta de mecanizado se realizaba cuando el número específico de piezas mecanizadas era superior a un umbral. Por lo tanto, una estrategia predictiva era muy interesante para este tipo de procesos.

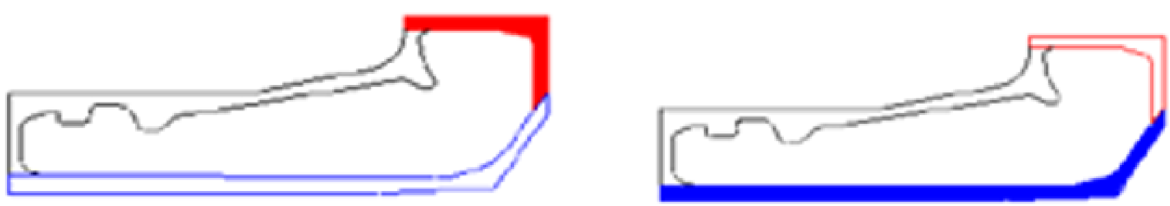


Figura 3.4: Torneado exterior (derecha) e interior (izquierda) realizado por el centro de torneado.

Dentro de este proyecto se han realizado numerosos estudios y pruebas para la predicción de vida útil remanente de la herramienta de corte. Desde los primeros pasos de procesado de los datos hasta la elección de un algoritmo basado en datos para la prognosis.

Dentro del procesado de datos se realizó una reducción de dimensionalidad mediante la caracterización de las señales de corte. Para ello se utilizaron varios valores estadísticos, una eliminación de outliers aplicando la metodología de Maronna et al. (2006) y un estudio entre diversos métodos de suavizado de señales entre los que se encuentran Savitzky and Golay (1964) y Extrapolation (1949) 2. En ambos suavizados se realizó un proceso de selección de parámetros óptimos y se compararon ambos para la selección del más idóneo en este proceso. La caracterización se hizo con ayuda experta y dentro de los estadísticos elegidos se realizaron varios estudios sobre la

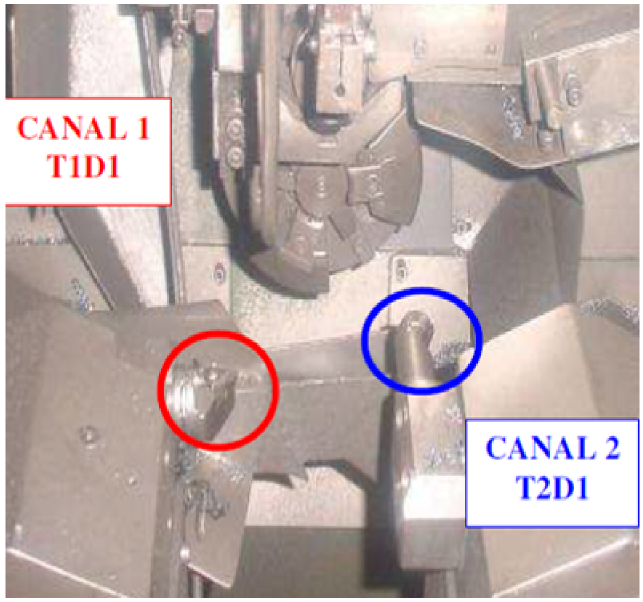


Figura 3.5: Imagen del centro de torneado con las dos herramientas.

importancia de cada uno en el proceso y la correlación entre dichos valores. Debido a la disposición de datos desde diciembre 2017 hasta mayo 2019, se planteó la detección de una posible deriva en el comportamiento de la máquina que pudiera generar un aumento en el esfuerzo requerido por la herramienta para la realización del torneado. Esta detección se basaba en el esfuerzo medio requerido al colocar una nueva herramienta y la tendencia de este esfuerzo a lo largo del tiempo. En los resultados obtenidos no se apreciaba tal deriva.

En lo que a la predicción de RUL se refiere, se realizaron varios modelos que se compararon entre sí con el fin de obtener aquel que permitiera una mejor aproximación offline. En la Figura 3.6 se aprecian las predicciones de varios modelos junto con el valor real. Los resultados obtenidos mostraron que las predicciones obtenidas por todos los modelos eran similares y se ajustaban adecuadamente a las variaciones reales de los sistemas.

Para la aproximación on-line del desgaste, se utilizaron aproximaciones polinómicas basándose en la literatura donde se estima un comportamiento polinómico en procesos de torneado. Se compararon la aproximación de segundo orden y la de primer orden, siendo esta última la que mejores resultados aportó en la validación. Para esta aproximación se desarrolló una herramienta web, donde el operador tiene la posibilidad de consultar una estimación del número de piezas restantes junto con valores históricos y otros estadísticos del proceso (véase Figura 3.7). Este resultado ha sido de gran valor para la empresa, ya que ha llevado a una implementación real del modelo en la máquina.

De este trabajo se obtuvo una publicación en una revista científica de impacto:

- Alberto Jimenez-Cortadi, Itziar Irigoien, Fernando Boto, Basilio Sierra, and GermanRodriguez. Predictive Maintenance on the Machining Process and Machine Tool. Applied Sciences, 10(1), 224. (2020)

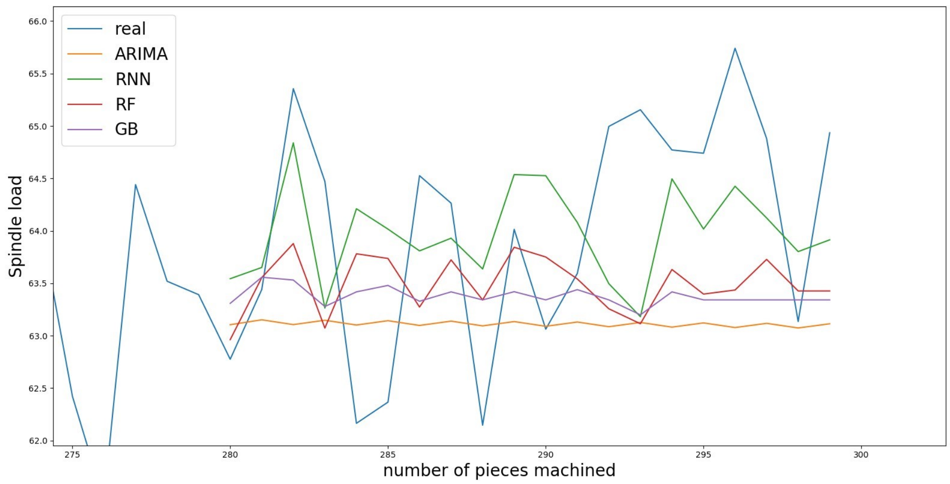


Figura 3.6: Comparación de distintos modelos para el cálculo de la prognosis.

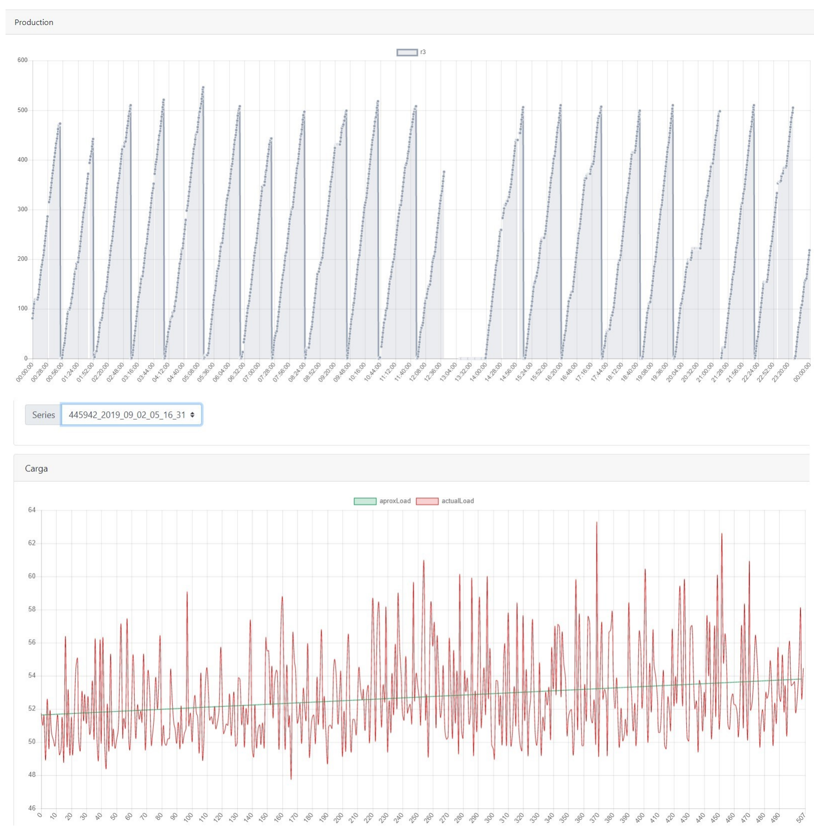


Figura 3.7: Visualizador disponible en producción.

3.3. Hibridación de datos y predicción de *RUL* en rodamientos.

En procesos de cálculo de *RUL* uno de los principales problemas que se encuentran es el hecho de que todas las metodologías que se encuentran en la literatura son válidas únicamente para los procesos en estudio y no son generalizables. Con el objetivo de presentar una metodología que englobe parte de los problemas que se encuentran se ha desarrollado esta línea de investigación.

En este reto, se ha trabajado teniendo en cuenta los problemas típicos que se encuentran en un sistema real donde los datos son adquiridos durante el proceso. El problema principal en estos casos es la falta de datos asociados a todos los estados posibles del sistema y la pequeña cantidad de datos de los que se suele disponer. El primero de los problemas se debe al hecho de que los estados más críticos suelen acarrear grandes fallos en el sistema y junto con ello gastos económicos por lo que no se permite que el sistema los alcance.

En este proyecto se ha propuesto una solución a ese problema basado en la generación de datos sintéticos híbridos. La metodología propuesta tiene como base la disposición de unos datos reales asociados a un funcionamiento óptimo del proceso y el conocimiento, mediante literatura o experiencia, de las características asociadas a los estados críticos asociados a un determinado modo de fallo que se quiera estudiar. Estos datos reales son modificados para alcanzar valores asociados a otros estados de los cuales no tenemos mediciones o en casos en los que son mucho menores, caso de datos no balanceados.

Esos datos generados junto con los reales son utilizados para el entrenamiento de modelos asociados a datos. En este punto es donde se encuentra el segundo problema, la predicción de tiempo de llegada a fallo. Existen multitud de modelos que nos permiten realizar predicciones pero no existe un modelo genérico para un problema tipo. Por ello y sabiendo que los modelos híbridos permiten fusionar cualidades de varios modelos, se ha planteado una modelización híbrida de varios modelos para la solución del mismo. La validación se ha realizado mediante la generación de una degradación del sistema y la predicción del modelo para diferentes ventanas temporales.

Esta metodología se ha aplicado a un rodamiento (ver Figura 3.8) en el cual se ha estudiado el modo de fallo asociado al anillo exterior y las muescas que pueden surgir por el rozamiento de las bolas. Para ello se disponen de datos asociados al funcionamiento del rodamiento, los cuales han sido adquiridos mediante un acelerómetro que mide las vibraciones del mismo.

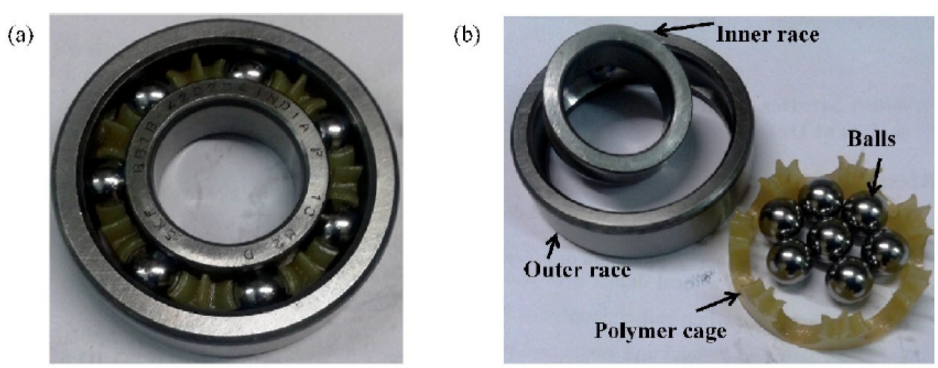


Figura 3.8: Ilustración de un rodamiento (a) y sus componentes (b).

Los datos son adquiridos en el dominio temporal (ver Figura 3.9) pero debido a que el modo de fallo viene caracterizado en el dominio frecuencial, se ha realizado una transformación de

Fourier para la señal. Una vez en el dominio frecuencial se han modificado las señales reales en unas frecuencias determinadas para obtener las señales sintéticas asociadas a los estados no representados. Entre ambos dominios, se ha realizado una caracterización mediante estadísticos básicos que permite definir cada estado de manera más sencilla. Con el objetivo de realizar un diagnostico y confirmar que las señales generadas corresponden a cada estado, se realiza un calculo de centroides (K-medias) y se confirma el estado de cada señal generada mediante el cálculo de la distancia mínima a los centroides, esto es, aquel centroide que se encuentre más cerca definirá el estado del sistema.

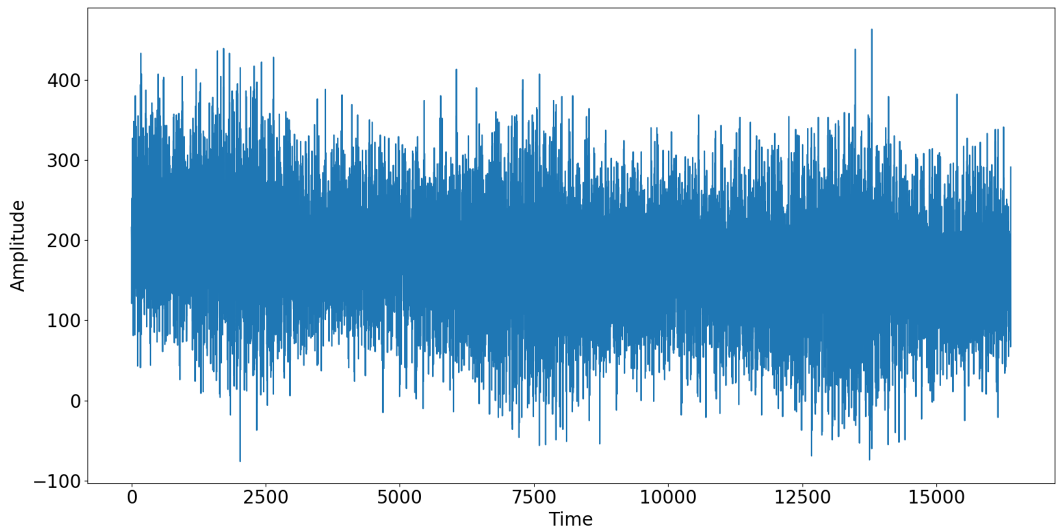


Figura 3.9: Datos adquiridos en el dominio temporal.

Para el cálculo de RUL se han utilizado 3 modelos simples que finalmente se han fusionado mediante un modelo híbrido. Los resultados se muestran en la Figura 3.10 donde se aprecia que todos ellos siguen en mayor o menor medida la señal real de manera correcta. Con la argumentación mostrada anteriormente se ha decidido utilizar el modelo híbrido y se validan sus resultados a través de los resultados obtenidos en un modelo de degradación generado para este modo de fallo.

Cuadro 3.1: Estimación del RUL, el valor real y el error cometido. También se muestra la desviación estándar y la probabilidad de que haya un fallo en el momento actual.

	Real	**Predicho**	**Error**
RUL	8.596	8.315	**0.281**
Desviación estándar, σ	4.060	3.285	**0.775**
Probabilidad, $P(\%)$	68.383	63.056	**5.327**

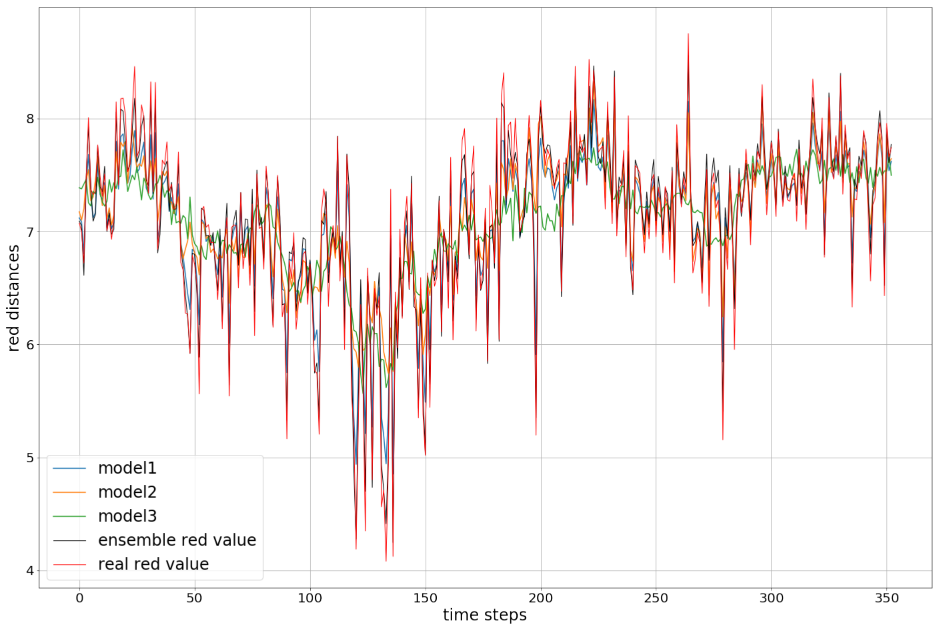


Figura 3.10: Comparación de los resultados obtenidos por cada modelo y el valor real.

Los resultados (Cuadro 3.1) muestran que se ha obtenido un modelo con una gran capacidad de predicción y que modela adecuadamente el sistema. Esta metodología se ha pretendido realizar de una manera más genérica que las disponibles actualmente y es por ello que se considera capacitada para ser extendida a otros modos de fallo y otros sistemas.

De este trabajo se ha realizado una publicación que se encuentra bajo revisión.

- Alberto Jimenez-Cortadi, Alberto Diez-Olivan, Itziar Irigoien, Dammika Seneviratne, Itziar Landa-Torres, Iñigo Reiriz-Irulegui, Fernando Boto, Orlando Peña, Iñaki Garcia, Marc Vila and Diego Galar. **A hybrid approach for synthetic data generation and advanced prognostics.**. IEEE TRANSACTIONS and JOURNALS, 2020.

3.4. Otras líneas de investigación

A parte de las lineas de investigación mencionadas previamente, también se ha colaborado en otros proyectos de investigación dentro de Tecnalia en el ámbito del mantenimiento en la industria. Se han conseguido diferentes hitos y se ha colaborado en aportaciones para otras tesis doctorales.

3.4.1. Desarrollo de un controlador para aerogeneradores.

Esta línea de investigación se ha centrado en la optimización y modelización de un aerogenerador desde el punto de vista del mantenimiento. El sistema de control del ángulo pitch tiene la función de regular la aerodinámica de las palas para controlar la absorción de energía del viento. El sistema de control del ángulo pitch tiene dos objetivos contradictorios: i) maximizar la absorción de energía eólica ii) minimizar la fatiga mecánica y estructural. Debido a que los objetivos son contradictorios, no existe una estrategia única.

Se han desarrollado unos modelos aerodinámicos, estructurales, mecánicos y eléctricos adecuados para simular el comportamiento de un aerogenerador.

- Se muestran varias estrategias de control (11 estrategias diferentes) para el control del pitch.
- En base a los objetivos (maximizar la energía y minimizar la fatiga), se propone cuatro métricas diferentes para evaluar las estrategias del ajuste del controlador del pitch.

Con el objetivo de maximizar la corriente entregada a la red eléctrica se han desarrollado modelos que permiten minimizar la aceleración angular del rotor (la velocidad angular sea constante para evitar fatigas), minimizar el movimiento pitch de las palas y minimizar las variaciones de longitudinales de fuerza.

En la colaboración que se realizó se obtuvo un articulo científico de alto impacto:

- Asier González-González, Alberto Jimenez Cortadi, Diego Galar, and Lorenzo Ciani. Condition monitoring of wind turbine pitch controller: A maintenance approach. Measurement, 2018.

3.4.2. Optimización de refinerías mediante algoritmos genéticos.

El objetivo principal del proyecto que sostiene el trabajo en esta línea, es la reconversión de dos tipos de hornos industriales, alimentados actualmente con gas natural, aplicados en tres sectores de gran consumo energético. Así pues, este proyecto tiene por objeto diseñar, aplicar y validar una solución integrada de adaptación avanzada para aumentar la eficiencia energética y ambiental en los hornos industriales de precalentamiento y fusión existentes alimentados actualmente con gas natural; mediante la aplicación combinada de nuevas soluciones basadas en materiales de cambio de fase, refractarios inocuos para el medio ambiente, combustión de gas natural y gas de síntesis procedentes de la biomasa y un sistema avanzado de vigilancia y control basado en los datos recogidos del proceso.

El resultado obtenido relacionado con el proyecto de tesis doctoral que aquí se expone es la realización de una búsqueda exhaustiva de algoritmos genéticos aplicados en refinerías y una clasificación de los mismos en términos de mayor aplicación en la literatura, sugiriendo un algoritmo para cada estudio requerido en estos sistemas. Esto ha aportado gran conocimiento al respecto de los algoritmos genéticos y posibles aplicaciones en futuros proyectos.

3.4.3. Desarrollo de modelos híbridos para procesos industriales.

El objetivo principal del proyecto es la investigación en tecnologías y la generación de conocimiento científico-tecnológico que permitan en un futuro no menor a 5 años, el desarrollo de modelos avanzados (físicos e híbridos), para la mejora de la vida de componentes y bienes de equipo que permitan evaluar el comportamiento de dichos sistemas durante su vida en función de las condiciones de uso, de tal forma que se aumente la fiabilidad, se extienda la vida de los activos a la vez que se reduzca el coste global de desarrollo y mantenimiento del producto para las empresas.

El trabajo realizado dentro de este proyecto de tesis se ha basado en la búsqueda de algoritmos híbridos aplicados en el ámbito del mantenimiento predictivo y la aplicabilidad de estos en función del sistema en estudio. De este estudio se han obtenido conocimientos avanzados tanto sobre la hibridación como sobre sus aplicaciones en la industria y se han obtenido competencias básicas para su aplicación en futuros proyectos.

3.4.4. Diagnóstico de fallos en estampación en frío.

El proyecto se dispone dentro del sector de estampación en frío donde el objetivo es la generación de un modelo que permita la prognosis en la rotura de herramientas para así sustituir el mantenimiento correctivo inicial. Para la generación de este modelo es imprescindible la extracción de información de los sistemas de control de las máquinas, así como el tratamiento de los datos combinando las técnicas clásicas y el tratamiento de “series temporales”.

La estampación en estudio disponía de seis etapas tras las cuales se obtenía una pieza de pequeño tamaño. La motivación para realizar este estudio es la gran inestabiliad del proceso, los costes en utillaje y la pérdida de tiempo productivo casusado por una parada, debido a un problema grave en la máquina. El primer paso a realizar en este proyecto fue la segmentación de dichas etapas, de las cuales se habían medido las fuerzas durante el proceso. Una vez segmentadas se realizó una caracterización de las señales asociadas a los golpes mediante unos estadísticos básicos (media, área, máximo,...). Con todas esas variables se construyo una matriz de valores para cada una de las etapas.

La idea del trabajo en esta línea era crear indicadores de monitotrización basada en la condición para estimár cuándo se iba a producir un problema grave en la máquina. Debido a la naturaleza no supervisada de los datos, el diagnostico de fallos se realizó mediante técnicas de agrupación. La idea subyacente era crear esos grupos mediente técnicas de clustering para estimar la normalidad del proceso. A partir de aquí, la similitud a estos grupos de normalidad permitía obtener esos indicadores con unas tendencias que terminaban en un problema grave en el proceso.

Los resultados fueron expuestos en un congreso internacional; Intelligent maintenance for industrial processes, a case study on cold stamping. Boto, F., Lizuain, Z., & Cortadi, A. J. (2017, September). In International Joint Conference SOCO’17-CISIS’17-ICEUTE’17 León, Spain, September 6–8, 2017, Proceeding (pp. 157-166). Springer, Cham.

3.4.5. Determinación de la huella de salud en procesos de estampación

El reto planteado en este proyecto es desarrollar el concepto de huella de salud aplicable a las prensas fabricadas por una empresa donde fabrican prensas hidráulicas y ejecutar un piloto para el mantenimiento predictivo en el subsistema de motor y bomba principales. Se plantea realizar el estudio en este subconjunto debido a su importancia en la máquina al tratarse del principal modo de accionamiento.

El trabajo realizado dentro de este proyecto de tesis hasta el momento ha consistido en la sincronización de diferentes datos. Estos datos son aquellos recogidos por el sistema durante su funcionamiento y datos asociados al mantenimiento y paradas del mismo. Junto con la sincronización de las señales, se han recogido aquellos modos de fallo que repercuten de manera más critica en el sistema, de tal forma que en el futuro del proyecto (aún en ejecución) se priorizará la adquisición de la huella de salud en estos fallos. Dicha huella de salud se basará en unas características asociadas al proceso que, mediante un estudio del sistema, permitirán determinar la velocidad de aproximación a los fallos conocidos del mismo. Para ello se tendrán en cuenta datos reales de proceso junto con datos sintéticos generados, para evitar un problema no balanceado, los cuales permitirán la determinación de la proximidad a cada fallo.

3.4.6. Sistema de monitorización y control inteligente para maquina inyectora de plástico

El objetivo principal del proyecto es encontrar la relación o ecuación de comportamiento, entre las variables medidas y la aparición y/o variación de grietas en las columnas, con el fin de evitar que se produzcan (y por consiguiente se evite la avería) o en caso de producirse se evidencie su evolución.

Dotar a la máquina de inyección de plástico de nuevas herramientas y capacidades, que permitan tener un mayor conocimiento del estado de la misma (condition monitoring), orientar la monitorización al mantenimiento, a la puesta a punto y al proceso.

El trabajo realizado dentro de este proyecto de tesis ha aportado un diagnostico de fallos durante el proceso de inyección de plástico. Para ello se analizaron las fuerzas sufridas por las 4 columnas asociadas a la inyección para diferentes modelos y las posiciones de las mismas. Estos valores han permitido determinar cuál de las columnas sufre un mayor esfuerzo. Debido a la ausencia de fallos y roturas en las columnas no se ha conseguido realizar un estudio más exhaustivo donde poder predecir una grieta o rotura de la misma.

3.4.7. Clasificación de procesos de torneado.

El proyecto se centra en la monitorización de procesos de torneado, donde se va a dotar a un sistema de la inteligencia necesaria para procesar, tanto los datos obtenidos por la sensórica, como datos procedentes de otras fuentes diversas, y generar la toma de decisiones. Para ello se implementarán algoritmos matemáticos para el análisis de grandes cantidades de datos (Big Data). A los datos aportados por los sensores de vibración y corriente se añadirán datos de otras o de nuevos tipos de sensores si fuera necesario, con el fin de lograr la máxima eficiencia en cuanto a costes y calidad para la fabricación de la pieza.

El trabajo realizado en el transcurso de este proyecto ha aportado un gran conocimiento en cuanto a los distintos procesos de torneado existentes. En una primera etapa se realizó una formación en los procesos aplicados en este proyecto y en muchos dentro de Tecnalia entre los cuales se encuentran los mencionados previamente (ver 3.1, 3.2 y 3.4.4). Este conocimiento permite adaptar de manera más eficiente los algoritmos aplicados a cada proceso.

El trabajo realizado comenzó con una segmentación de cada uno de los diferentes torneados en función de las posiciones del cabezal y esfuerzos realizados por cada herramienta. Este apartado ha sido de gran utilidad debido a que cada herramienta viene asociada a un proceso y la vida de la misma depende del numero de veces que se realice dicho proceso. Tras este segmentado, se han realizado estudios de la evolución del desgaste de cada herramienta asociando dicho desgaste al esfuerzo generado en cada torneado. Al ser un proyecto en ejecución, todavía está pendiente la realización de una predicción de desgaste y cambio de cada herramienta. Al contener más de una herramienta el cabezal, se pretende establecer una parada de máquina en la que cambiar más de una herramienta, de tal forma que la parada sea del menor tiempo posible.

CAPÍTULO 4

Conclusiones y trabajo futuro

4.1. Conclusiones y trabajo futuro

Desde la irrupción de la industria 4.0, la necesidad de reducir los tiempos de parada debido al mantenimiento ha crecido exponencialmente. Las empresas se han dado cuenta del potencial de realizar un mantenimiento óptimo y de la reducción de costes que esto produce. En el trabajo expuesto en este proyecto de tesis se ha trabajado para mejorar el mantenimiento en varios sistemas asociados a procesos de fabricación.

Dentro de los proyectos en los que se ha trabajado se han obtenido diferentes conclusiones aplicadas a cada entorno de trabajo. En todos ellos se han conseguido avances que permiten mejorar el mantenimiento actual realizado, generalmente basado en un contador o en revisiones periódicas, por uno basado en la condición del sistema o en la predicción de la evolución del mismo, lo que permite reducir costes y aumentar la eficiencia.

En un proceso de mecanizado de piezas de larga duración, se ha obtenido un modelo capaz de definir la normalidad y detectar el momento en el que el desgaste de la herramienta asciende de manera excepcional. El proceso no permite detenerse durante el transcurso del mecanizado y por lo tanto es de vital importancia detectar el momento en el que la normalidad se pierde. Esto permite evitar paradas debidas a un mantenimiento reactivo y sus consecuencias, que implican desechar la pieza en ejecución.

Dentro de los logros más representativos, se encuentra la creación de una aplicación de análisis visual capaz de predecir el número de piezas mecanizables restantes a la vez que acceso a un histórico de datos. El operario tiene la capacidad de consultar los datos y comportamiento del sistema en cualquier momento, lo que le ayuda a la hora de planificar sus tareas de mantenimiento tanto en este sistema como en otros de los que también se encarga. Esta aplicación ha permitido reducir el número de mantenimientos reactivos y el tiempo asociado a estas paradas. Previamente se disponía de un contador que alertaba al operario para que detuviera la máquina y realizará su mantenimiento. Ahora en cambio, le permite organizar las paradas de las máquinas y reducir el tiempo que permanecen detenidas, con su correspondiente aumento en la producción.

En términos de la hibridación de modelos, tema que día tras día aumenta en importancia, se han realizado hibridaciones tanto para la generación de nuevos datos como para la fusión de modelos de predicción. Estos modelos permiten recopilar las ventajas de varios modelos distintos en uno solo, lo que suele acarrear una mejor aproximación al modelo real. En cuanto a la generación de nuevos datos se ha desarrollado una metodología capaz de generar nuevos datos sintéticos basados en los datos reales y el conocimiento experto con el fin de solventar problemas no balanceados en los cuales la adquisición de datos se vea limitada.

Los trabajos realizados en otros proyectos han permitido la obtención de modelos de diagnóstico de fallos y determinación de huellas de salud en el ámbito de la estampación, diagnóstico de fallos en procesos de inyección de plásticos y la clasificación de distintos procesos de torneado en máquinas multietapa. Todos ellos aportan un salto de calidad en los proyectos asociados y han permitido mejorar los mantenimientos de las maquinas asociadas.

Tras la finalización de este trabajo y vistos los proyectos realizados, se plantean unas líneas de trabajo futuro como continuación de las mismas. Entre ellas se encuentran:

Se esta avanzando en la generalización de la metodología expuesta para la predicción de RUL en distintos sistemas. La validación se ha realizado en un rodamiento pero se plantea la posibilidad de extender esta metodología a cualquier proceso y sistema con unos parámetros similares. Se ha comenzado a estudiar un nuevo caso de uso en subsistemas asociados a una máquina de estampación.

Se ha realizado una comparación de modelos basados en datos para la predicción de RUL en series temporales obteniendo resultados similares para todos ellos. Esto propone varias nuevas líneas de investigación; por un lado la mejora de modelo que puede realizarse mediante el desarrollo de nuevos modelos de datos que permitan mejorar los resultados obtenidos o el desarrollo de un modelo híbrido con los modelos existentes para la obtención de dicha mejora. Por otro lado se plantea la posibilidad de obtener una mayor sensórica y más datos relacionados de tal forma que la calidad de los mismos aumente y esto repercuta en los resultados.

Se plantea la caracterización de huellas de salud asociadas a diferentes procesos y el estudio de la evolución de estas, de manera que al realizarse un mantenimiento se reconozca la mejoría en el sistema y adaptar la predicción de RUL a estos eventos. La caracterización de estas huellas de salud son altamente dependientes del sistema en estudio pero se está trabajando en una caracterización asociada a elementos rotativos basada en sus vibraciones que podría ser extensible a múltiples sistemas.

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Parte II

PUBLICACIONES

CAPÍTULO 5

Artículos científicos

5.1. Estimación de la vida útil remanente en superaleaciones

5.1.1. A statistical data-based approach to instability detection and wear prediction in radial turning processes

- **Título**: A statistical data-based approach to instability detection and wear prediction in radial turning processes.
- **Autores**: Alberto Jimenez Cortadi, Fernando Boto, Alfredo Suarez, Diego Galar, Itziar Irigoien, Basilio Sierra
- **Revista**: Eksploatacja i niezawodnosc - maintenance and reliability
- **Año**: 2018
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Radial turning forces for tool-life improvements are studied, with the emphasis on predictive rather than preventive maintenance. A tool for wear prediction in various experimental settings of instability is proposed through the application of two statistical approaches to process data on tool-wear during turning processes: three sigma edit rule analysis and Principal Component Analysis (PCA). A Linear Mixed Model (LMM) is applied for wear prediction. These statistical approaches to instability detection generate results of acceptable accuracy for delivering expert opinion. They may be used for on-line monitoring to improve the processing of different materials. The LMM predicted significant differences for tool wear when turning different alloys and with different lubrication systems. It also predicted the degree to which the turning process could be extended while conserving stability. Finally, it should be mentioned that tool force in contact with the material was not considered to be an important input variable for the model.

A statistical data-based approach to instability detection and wear prediction in radial turning processes

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Abstract

Radial turning forces for tool-life improvements are studied, with the emphasis on predictive rather than preventive maintenance. A tool for wear prediction in various experimental settings of instability is proposed through the application of two statistical approaches to process data on tool-wear during turning processes: *three sigma edit rule* analysis and *Principal Component Analysis* (PCA). A *Linear Mixed Model* (LMM) is applied for wear prediction. These statistical approaches to instability detection generate results of acceptable accuracy for delivering expert opinion. They may be used for on-line monitoring to improve the processing of different materials. The *LMM* predicted significant differences for tool wear when turning different alloys and with different lubrication systems. It also predicted the degree to which the turning process could be extended while conserving stability. Finally, it should be mentioned that tool force in contact with the material was not considered to be an important input variable for the model.

Keywords: Radial turning, Tool-life improvement, Instability detection, Wear prediction, Linear Mixed Models

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1. Introduction

New lighter and thinner alloys may be found in innovative aerospace, rail, and automotive components, among other industrial products. Generally known as superalloys, these materials can withstand higher temperatures and mechanical stress levels than ordinary alloys and are designed to reduce consumption and to increase productivity.

Superalloys are categorized as hard turning materials with a hardness index of at least 45 on the Rockwell C-scale *HRC*. The process of turning such alloys, produces high mechanical and thermal stress on cutting tool inserts, which influence cutting force, tool wear, surface integrity, and the accuracy of machining processes.

Although these materials in themselves will entail process instability, monitoring of tool conditions can detect both material and process-related instabilities. Reliable predictions can therefore be made using the same data sets. Process instabilities are often recorded at increased vibratory amplitudes, provoking undesired tool failures among other events that can damage both the workpiece and the machine tool [13].

Tool condition monitoring can track tool wear and thereby predict the Remaining Useful Life (*RUL*) of the tool, a very important issue for rapid machining processes involving superalloys. Together with the detection of instability, tool monitoring provides a valuable data source for improving the efficiency of superalloy turning processes.

In this paper, cutting-force signals are studied for the detection of instabilities during the hard-turning process and a tool-wear prediction model is proposed. The three superalloys tested in this study were as follows: *Inconel 718*, *Haynes 282* and *Waspalloy*.

The structure of this paper will be as follows. In Section 2, related work on radial turning process optimization, tool-wear prediction, and the improvement of tool life will be discussed. In Section 3, the industrial application will be explained and, in Section 4, the methodology used to detect instabilities and to predict tool wear. The results will be presented in Section 5. Finally, the conclusions will be discussed in Section 6.

2. Related Work

Many investigators have been exploring ways of predicting cutting-tool behaviors *RUL*, by establishing the length of time certain tooling processes will withstand wear [1]. *RUL* is the analysis of the remaining working time and number of executions of a tool, at a particular working age. The resulting information is used to predict whether the tool can still machine the piece to an acceptable finish. [15] developed a proportional hazard model for the remaining useful life of 25 identical tools during the turning of titanium metal matrix composites. The remaining useful life curves were developed for two different machining conditions: cutting speed and feed rate. [9] analyzed tool wear in the finish turning of AISI 1045 steel under different cooling conditions, to conclude that minimum quantity cooling lubrication (*MQCL*) provided significant improvements in the wear rate of the cutting tool and its productivity. [7] estimated the *RUL* of a bearing process with artificial neural network models that produced better bearing failure performance predictions. [19] compared multiple machine learning algorithms for tool-wear prediction and concluded that Random Forest generated higher accuracy than Artificial Neural Networks and Support Vector Regression. [11] developed mathematical models for describing surface finish and flank wear, employing multiple linear regression analysis during ceramic-tool machining of AISI-D2 steel. The nose geometry of the cutting tool strongly influenced the productivity and surface finish of the hard-turning process. [6] developed an online Neural Network model for tool-wear monitorization based on force ratio and cutting conditions. The algorithm was successfully verified during turning. [12] estimated tool conditions by applying neuro-fuzzy techniques, which yielded the best results for tool-wear estimation with cutting force and machining time variables. [20] developed a model based on particle-swarm optimization that fitted better than the back-propagation neural network for tool-life prediction.

Although tool-life prediction and *RUL* estimation are important in machining processes, stability is also one of the main topics for achieving the aim of obtaining good quality pieces, due to the fact that even if the remaining useful life of the tool is good, an instability may cause a machine failure. On this topic, [14] proposed a linear stability analysis in the frequency domain based on cutting forces. [4] developed a linear model based on the root locus method, called a chatter model for predicting stability in hard-turning processes. [17] proposed a method for measuring the stability of cutting processes that applied the power-spectrum density of dynamic cutting forces.

As may be seen from this literature review, many technologies have been developed over the years to predict tool wear, to improve tool life, and to detect stability during machining processes. Most of these technologies have been applied to a particular fault and have yielded good results for both stability and wear prediction. A hybrid mix of both predictive approaches is proposed in this paper, which will enable better prediction for stable tests and will prevent possible failure modes related to instability.

3. Industrial Application

This study is based on a radial turning process, applied to nickel-based superalloys. Even though only nickel-based superalloys enter into the case study (*Waspalloy*, *Inconel 718* and *Haynes*), the chemical composition of the superalloys differs slightly. Cutting tests were conducted at 30 m/min cutting speed, with a depth of cut of 2 mm and a feedrate of 0.1 mm/revolution. Each test had the same total amount of removed material, with a spiral cutting length (SCL) of 727 m, divided into six or four passes depending on the alloy. Standard uncoated cemented carbide inserts (Sandvik CoromantTCMW16T304, grade Sandvik H13A equivalent to ISO S20) were used with 0.4 mm tip radius.

The above-mentioned superalloys can be found in a wide variety of states, obtained by thermal heating and cooling processes. Annealing is the one that we will consider in this study. The physical process of annealing produces microestructural changes that include recrystallization and grain growth [5]. The crystallization structure of alloys treated at high temperatures and for long annealing periods will break up and the subsequent recrystallization processes will differ, depending on the rapidity of the annealing or cooling process. Note that while grain growth can be provoked through heat treatment, the same is not true for the reduction of grain size. Recrystallization and grain growth processes can both be controlled by regulating the heating and the cooling times.

Two states of grain size *Large Grain* (LG) and *Small Grain* (SG) can be distinguished in Figure 1. In terms of strength, *Aged* (A) refers to a stronger state than and *Solutioned* (S).

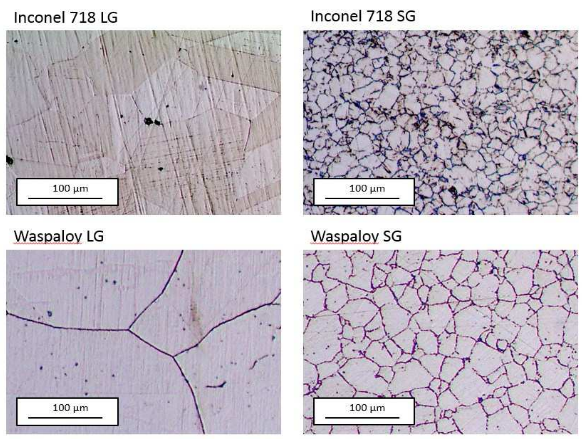


Figure 1: Structural differences at a microscopic level between *LG* and *SG* in different superalloys.

Turning processes require lubrication to reduce high temperatures and to extend the life of tools subjected to high torque forces during the machining process. Both [16] and [10] discussed lubrication in their studies. In this case, the selected parameters for temperature reduction were a *conventional lubrication system* at a pressure of *6 bars* and a High Pressure Coolant *(HPC)* system at a pressure of *80 bars*. In radial turning processes, a pass is considered finished when the tool has moved from the surface of the material to the final point on the axis. A pre-determined number of passes made sequentially are called a test. The number of passes needed to complete a full test differed in acccordance with the materials that were studied in this paper. 6 passes were required to complete a test on *Inconel 718* and *Waspalloy*, while 4 passes were needed for *Haynes*. Table 1 shows the number of tests for each superalloy, the grain size, and the lubrication systems.

		SGS	SGA	LGS	LGA
Inconel	Conventional	2	2	2	2
	HPC	-	3	-	2
Haynes	Conventional	-	-	2	2
	HPC	-	-	1	1
Waspalloy	Conventional	2	2	1	1
	HPC	1	1	1	1

Table 1: Number of tests for each superalloy (Inconel, Haynes, Waspalloy), grain size, strength (SGS, SGA, LGS, LGA) and type of lubrication (Conventional, HPC).

The initial conditions set up in this study were the same for every superalloy in every state.

While each pass was running, the cutting force of the tool in contact with the superalloy was measured. This force was then decomposed into three components, *Fx, Fy, Fz*, which were perpendicular to each other. Once a pass had finished, tool wear was also measured, in two different ways: *flank wear* and *notch wear*. *Flank wear* was measured at nine different points where the tool enters into contact with the superalloy. *Notch wear* appears just after *flank wear* and is usually larger. Note that only *flank wear* is studied in this paper. *Notch wear* was not studied, due to it having no relation with the force signals generated during the process that are a key focus of this study.

Figure 2 illustrates, the three force components. These signals are taken from one particular pass: in general, the signals from any of the passes will be of a similar appearance.

The main purpose of this paper is to predict tool wear under different settings. Given the direct relationship between tool wear and process stability, we study process instability in terms of the force signal; not only for the complete test but also for each pass. Then we create a linear mixed model to compare the wear for different setting situations and to predict the expected wear.

Note that an expert will be able to label each complete pass as either stable or unstable. Once a pass is labeled as unstable the whole test is considered unstable.

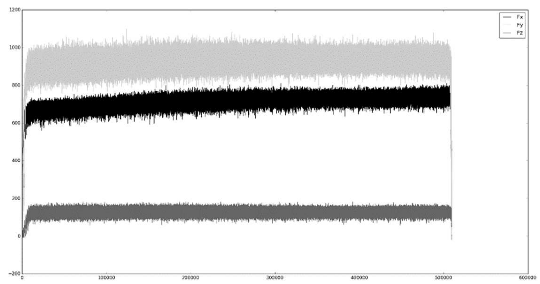


Figure 2: Measured forces for a single pass for the three components.

4. Methodology

In this study, we have two goals: to identify the instability that can occur in irregular turning processes; and, to identify tool wear, the critical parameter during the turning process. The following sections explain the methodology to reach each goal.

4.1. Instability Detection

Instability has a direct relationship with tool wear linearity. An unstable process results in non-linear tool wear, causing a disturbance in the process.

First, we studied stability in each pass of every test, independently. Then, we analyzed the stability of the full test composed of several passes, comparing a given pass with the first pass, previously identified as stable or unstable.

4.1.1. Instability detection of a pass

Let the signals of the force components of a pass p be $(F_{xt}(p), F_{yt}(p), F_{zt}(p))_t$, recorded at a series of time-points $t = 1,...T$ for passes $p = 1,...,6$. The instability of any one given pass, p, must be detected. The instability of a pass is closely related to the outlying data values of the force components that were analyzed with the *three-sigma edit* rule [8].

This simple robust method allows us to obtain the median value of each force component, Me_c = $Median_t\{F_{ct}(p)\}$, and the corresponding absolute standard deviations, and can be expressed as:

$$|F_{ct}(p) - Me_c|, \qquad t = 1,...,T;\ c = x,y,z,$$

where, c is the axis of the force, t is the machined piece, and p is the pass.

The median value of these deviations is calculated and divided by 0.6745 as indicated in [8]:

$$MADN_c(p) = \frac{Median_t\{|F_{ct}(p) - Me_c|\}}{0.6745}$$

The robust three-sigma edit rule (see [8]) establishes that observation $F_{ct}(p)$ is an outlier, if

$$|F_{ct}(p) - Me_c| > r,$$

where, r is a threshold value. Under the normality assumption, r = 3 is often set (hence the "three-sigma rule") and any observations beyond that threshold are considered outliers. Based on the three-sigma edit rule, a component force, c, at pass, p, is considered unstable, if:

$$Max_t\left\{\frac{|F_{ct}(p) - Me_c|}{MADN_c(p)}\right\} > r. \tag{1}$$

In the case studied here, pass p is considered unstable if at least 2 of the 3 force components x, y or z are considered unstable. We explore different threshold values to establish the best one in this case. The goodness-of-fit is measured by the accuracy between the label given by the proposed approach (stable/unstable) and the expert's label. It is determined by a confusion matrix (Table 2), where the rows show the predicted values and the columns show the expert classification. Accuracy is given as a percentage value representing an approximation between the state predicted by the approach and expert classification.

	Real class	
Pred. class	Stable	Unstable
Stable	T_p	F_p
Unstable	F_n	T_n

Table 2: Confusion matrix in a classification problem.

$$Accuracy = \frac{Tp + Tn}{Tp + Tn + Fp + Fn} \quad (2)$$

The variability of the accuracy was measured by a moving blocks bootstrap approach [18]. This statistical technique is used to obtain bootstrap samples from correlated data. The signal is divided into contiguous blocks of length L. Following sampling with replacement from the blocks, the signals were then processed with a bootstrap technique. In this process, the threshold providing the highest accuracy is considered as the optimum value to detect the instability of a pass .

In this study, the above approach is only applied to the first pass of each test, due to the importance of this pass in the stability of the whole test.

4.1.2. *Instability detection of a whole test*

In this section, an instability-detection method is used to analyze the stability of the whole test. The approach is based on the comparison of any given pass of the test with the corresponding first pass of the test. First, the classical statistical technique of Principal Component Analysis (PCA) [3] is applied to reduce the dimension from the 3 force components to only two dimensions, so that the full signal of forces of the first pass can be easily visualized. PCA is based on combining linearly input features, in this case the force components of the first pass ($F_{ct}(1)$, $t = 1,\ldots,T$; $c = x,y,z$), to obtain new ones ($C_k(1)$, $k = 1,2$) that are linearly independent between each other and maintain as much of the original information as possible. Second, subsequent passes are projected on the same space, so the progress of the test can be seen graphically. In addition to graphical classification, a quantitative measure is calculated: given $F_t(p) = (F_{xt}(p), F_{yt}(p), F_{zt}(p))$, the maximum distance from any time point, t, of this pass, p, to the centroid of the first pass is as follows:

$$D(p) = \max_t \left\{ \sqrt{\sum_c (F_{c,t}(p) - \overline{F_c(1)})^2} \right\}.$$

These distances are obtained for each test and are used to determine the stability of the test; as a result, the test will be classified as unstable when the value $D(p)$ is twice the value of $D(1)$ in the first pass.

Validation of this model is done by comparing the stability classification that is obtained with the one offered by the expert. To do so, the confusion matrix is calculated and an accuracy value is obtained.

4.2. Tool-wear prediction

In this section, the objective is to model the radial turning according to some of the variables sensorized during the process and some others that depend on the material. Throughout the turning process for each piece, the wear at the end of each pass is recorded. The effect of each pass is the most important variable to take into account to build a model for the evolution of the wear. Nevertheless, factors that include the type of alloy, grain size, lubrication pressure, as well as forces on each component are considered. Since the wear is measured several times on the same piece or tool along the turning process, these measurements may be correlated. A linear mixed-effect model (LMM), capable of properly processing the data correlations, generated the model of tool wear.

A brief explanation would be that the dependent variable $\mathbf{w} = (w_{ip})_{ip}$ (in this study the wear, where w_{ip} stands for the tool wear, i, at the end of a pass, p) is formulated within the following general model in an LMM:

$$\mathbf{w} = \mathbf{X}\beta + \mathbf{Z}\mathbf{b} + \epsilon, \qquad \mathbf{b} \sim N(\mathbf{0}, \mathrm{D}) \text{ and } \epsilon \sim N(\mathbf{0}, \mathcal{R}),$$

where $\mathbf{X}$ is a $n \times k$ matrix (k is the number of fixed effects), $\mathbf{Z}$ is a $n \times q$ matrix (q is the number of random effects) and D is the variance-covariance matrix ($q\times q$) of the random effects. The random effects (which are modeled by random variables) in these models permit the prediction of the behavior of particular units in the sample, as well as an estimation of variability between different units.

Inference for the model selection was performed with the Likelihood Ratio (LR) test for the fixed effects and by chi-squared distributions derived from Restricted Maximum-Likelihood Estimation-based LR tests for variances and covariances of the random effects (see [2] for details). The diagnosis of the model was not done by the analysis of the residuals. Instead, the Normalized Root Mean Square Deviation (NRMSD) statistic was used, to give a quantitative value of the approximation, where lower values indicate less residual variance.

5. Results

The results are organized into two main sections. In the first one, the results on instability detection are shown and, in the second, those concerning tool wear.

5.1. Instability Detection

As a first step, we studied the time series signal of each first pass considering different threshold values in equation (1). As mentioned in section 4.1.1, a threshold value has been searched for, in order to determine the optimum value for this specific process. The stable/unstable label obtained was compared with an expert opinion and the accuracy value was calculated. The standard deviation of the accuracy was measured on 200 bootstrap samples (see Table 3).

Threshold	Accuracy(std)
3	0.28 (0.000)
5	0.28 (0.032)
7	0.72 (0.047)
8	**0.82 (0.039)**
9	0.79 (0.017)
10	0.79 (0.018)

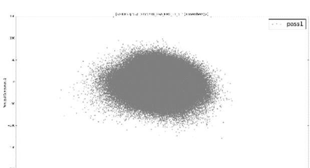
Table 3: Accuracy value and its bootstrap estimated standard deviation (std) for different thresholds.

The results showed that the best threshold value was $r = 8$. Moreover the approach was not dramatically sensitive to the threshold value and values above $r = 8$ also yielded comparable results.

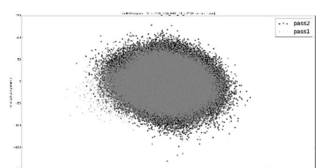
As a second step, the stability of the test based on the first pass was studied. The technique of Principal Component Analysis (PCA) produced a global summary of the forces in graphic form. Two PCA analyses can be seen in Figures 3 and 4, which present all the passes of a test for stable and unstable tests, respectively. A test is considered unstable when a particular value $D(p)$ of any pass, p, is over twice the maximum distance of the first pass, $D(1)$.

The maximum distance from the first pass centroid to any of the points of each pass is shown for both stable (Figure 5a) and unstable tests (Figure 5b). These values were obtained for the rest of the tests and the results following their comparison with the expert stability classification are shown in Table 4.

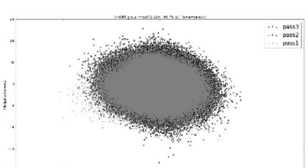
In Table 4, it can be seen that most of the tests are well classified, which accounts for 76% of the accuracy, calculated as the percentage of well classified values divided by the sum of all values (see equation. 2).



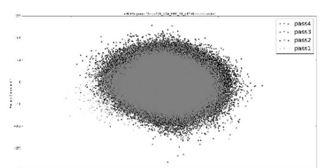
(a) Pass 1.



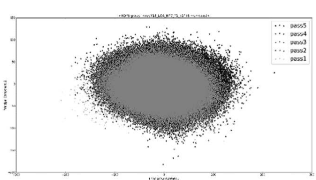
(b) Pass 2.



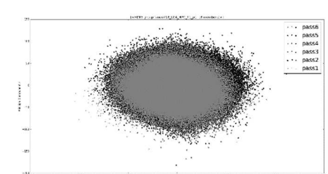
(c) Pass 3.



(d) Pass 4.



(e) Pass 5.

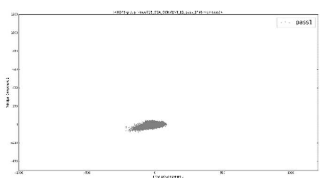


(f) Pass 6.

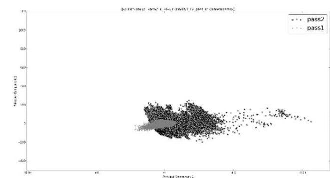
Figure 3: Principal Component Analysis of a stable test, composed by 6 stable passes.

	Expert's classification	
Pred. class.	Stable	Instable
Stable	13	5
Instable	2	9

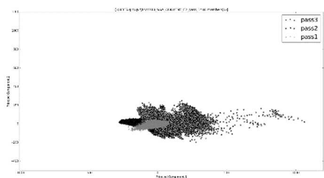
Table 4: Confusion matrix comparing the classification given by the expert (columns) and the obtained (rows) by comparing the maximum distances from the centroid of the first pass to the others: $D(p)$.



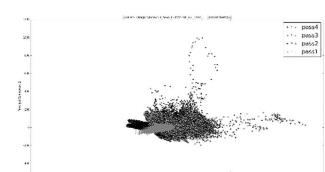
(a) Pass 1.



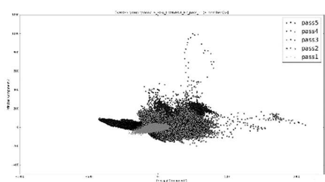
(b) Pass 2.



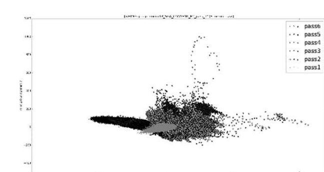
(c) Pass 3.



(d) Pass 4.

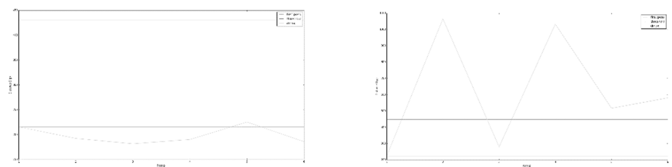


(e) Pass 5.



(f) Pass 6.

Figure 4: Principal Component Analysis of an unstable test. The same axis in each of the 6 passes is shown, to highlight the variability of this process.



(a) Stable test. (b) Unstable test.

Figure 5: Maximum distance to the centroid of the first pass D(1) for each pass D(p).

5.2. Tool-wear prediction

During the radial turning process, each tool, *i*, is related with its experimental setup conditions ($i = 1,...,29$). Particularly, the type of superalloy and the lubrication system were of significant importance for tool wear throughout the model selection process, although the same could not be said for grain size, strength, and the forces that the tool withstands. Taking all these issues into account, the fitted model is as follows:

$$\begin{aligned} w_{ip} = {} & \beta_0 + \beta_1 \mathrm{Haynes}_i + \beta_2 \mathrm{Waspalloy}_i + \beta_3 \mathrm{Conventional}_i + b_{0i} \\ & + (\beta_4 + \beta_5 \mathrm{Haynes}_i + \beta_6 \mathrm{Waspalloy}_i + \beta_7 \mathrm{Conventional}_i) p + b_{1i} p \\ & + \epsilon_{ip}, \end{aligned}$$

where:

- w_{ip} is the wear of the *i*th tool at the end of the pass *p*,
- Haynes_i and $\mathrm{Waspalloy}_i$ are dummy variables that indicate the type of superalloy that the *i*th tool is cutting, and $\mathrm{Conventional}_i$ is the dummy variable for the lubrication system of the *i*th tool,
- the random effects of the model are
$$\begin{pmatrix} b_{0i} \\ b_{1i} \end{pmatrix} \sim N(\mathbf{0}, \mathcal{D}) \quad \text{with} \begin{pmatrix} d_{11} & 0 \\ 0 & d_{22} \end{pmatrix},$$
- the errors of the model have 0 mean but are heterocedastical
$$VAR(\epsilon_{ip}) = \sigma^2 \theta_i^2$$

  with $\theta_i^2 = 1$ if the *i*th tool is stable and $\theta_i^2 \neq 1$ otherwise.

The estimations of the parameters of the model and 95% approximate confidence intervals are in Table 5 as well as the *p*-values for the fixed effects. The latter are obtained by Maximum Likelihood.

	Parameter	Estimation	*p*-value
Fixed effects			
	β_0	83.1 (71.4, 94.8)	< .0001
Superalloy	β_1 (Haynes) β_2 (Waspalloy)	9.7 (-5.5, 25.0) -10.6 (-24.7, 3.6)	0.0032
Lubrication	β_3 (conventional)	-18.7 (-30.5, -6.9)	0.0213
Pass p	β_4	19.4 (12.9, 25.9)	< .0001
Superalloy×Pass	β_4 (Haynes ×p) β_4 (Waspalloy ×p)	-11.2 (-19.9, -2.6) -16.7 (-24.0, -9.4)	< .0001
Lubrication ×Pass	β_7 (conventional ×p)	13.1 (6.5, 19.7)	0.0001
Random effects	$\sqrt{d_{11}}$		
SD(b_{0i})	$\sqrt{d_{22}}$	10.9 (6.4, 18.5)	
SD(b_{1i})		8.5 (6.3, 11.4)	
Errors			
	σ	4.6 (3.7, 5.7)	
	θ_i	5.4 (4.2, 7.1)	

Table 5: Estimates of the LMM and approximate %95 confidence intervals

It is noteworthy that the variability between tools is much bigger than the residual variability, even for stable tests. For instance, by the intraclass correlation, 77% of the variability of the slope at each pass, *p*, is due to the variability between tools. Nevertheless, some general main effects can be assumed: each pass, *p*, on an *Inconel 718* alloy with HPC lubrication provokes mean tool wear of 19.4 mic. If the alloy is *Haynes* or *Waspalloy*, there will be less wear after each pass: mean average wear of 11.2 mic and 16.7 mic less, respectively. For a given alloy, when a conventional lubrication system was used, a higher mean wear of 13.2 mic compared with the HPC lubrication system was noted.

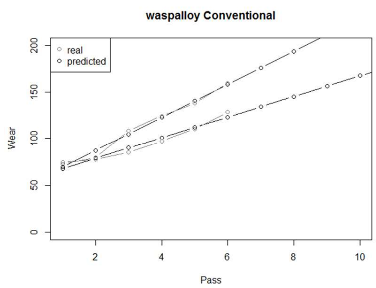
Using the model obtained and taking into account the maximum permitted tool wear (300 mic), it was easy to see that the tool could work properly with many more passes (a range from 10 to 81 passes depending on the tools). The prediction tendency for each of the tests is shown in Figure 6. The Normalized Root Mean Square The deviation measure (*NRMSD*) for the stable tests was 13.3%, which means that the mean percentage error for measured wear using LMM was 13.3%.

6. Conclusions

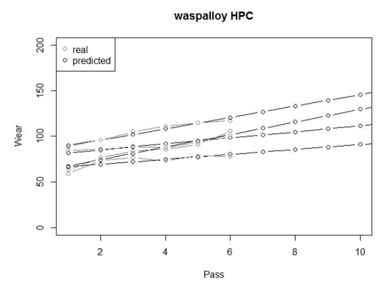
Two problems with a wide variety of industrial consequences for machining work have been discussed in this paper.

One aspect of this study is the development of a method for instability detection that can detect initial instability in radial turning processes. The three components of the measured force have been selected as the most important variables. These variables have been applied to two different methods with two goals; an off-line method, MADN, was used for first pass stability, which can be extended to the rest of the passes, and which produced an accuracy of 82% of the signals. Another methodology was based on PCA visualization, which provided an intuitive 2 dimensional representation of the forces. Applied on-line, it can function as a fault-detection method during machining processes and will, if necessary, end the process. The results applied to all the tests achieved an accuracy rate of 76%.

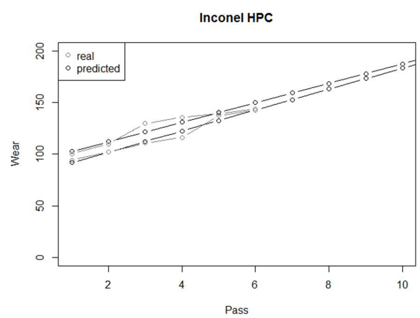
This result offers a better process-oriented view to the operator that is easier to understand. The algorithms can be directly integrated into the on-line monitoring tool, to analyze the effect of using a particular tool and material. The general approach in this work can be used in an experimental phase to improve the process with new materials.



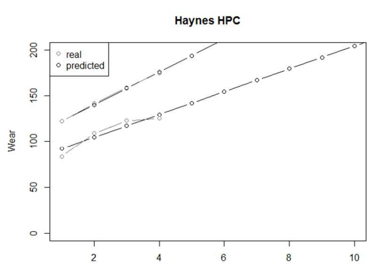
(a) Waspalloy Conventional.



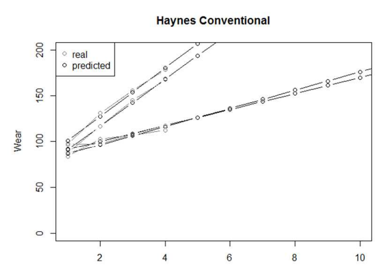
(b) Waspalloy HPC.



(c) Inconel HPC.



(d) Haynes HPC.



(e) Haynes Conventional.

Figure 6: Prediction of the tool wear for each test as a function of the material and the lubrication system.

A further aspect is that a tool-wear model based on a Linear Mixed Model has been applied. The model has shown that mean average tool wear differs, depending on the type of superalloy and lubrication system in use, as suggested in [16] and [10]. It is worth mentioning that the force of the tool in contact with the superalloy is not an important input variable in the model. The model has also been used to demonstrate that the tool can withstand a higher number of passes, with tool wear under 300 mic. while the stability of the turning process is held. As a consequence, the process could run longer without stopping, which would imply faster turning and less time to finish the piece. Finally, a confirmatory analysis using a larger amount of samples would be of interest, to reduce the uncertainty and variability of the different pieces.

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Conflict of interest

The Authors declare no conflict of interest

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5.1.2. Stability analysis of radial turning process for Superalloys

- **Title**: Stability analysis of radial turning process for Superalloys
- **Authors**: Jiménez, Alberto and Boto, Fernando and Irigoien, Itziar and Sierra, Basilio and Suarez, Alfredo
- **Journal**: Management Systems in Production Engineering
- **Publisher**: Sciendo
- **Year**: 2017

Stability detection in machining processes is an essential component for the design of efficient machining processes. Automatic methods are able to determine when instability is happening and prevent possible machine failures. In this work a variety of methods are proposed for detecting stability anomalies based on the measured forces in the radial turning process of superalloys. Two different methods are proposed to determine instabilities. Each one is tested on real data obtained in the machining of Waspalloy, Haynes 282 and Inconel 718. Experimental data, in both Conventional and High Pressure Coolant (HPC) environments, are set in four different states depending on materials grain size and Hardness (LGA, LGS, SGA, and SGS). Results reveal that PCA method is useful for visualization of the process and detection of anomalies in online processes.

Stability analysis of radial turning process for Superalloys

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***Abstract*—Stability detection in machining processes is an essential component for the design of efficient machining processes. Automatic methods are able to determine when instability is happening and prevent possible machine failures. In this work a variety of methods are proposed for detecting stability anomalies based on the measured forces in the radial turning process of superalloys. Two different methods are proposed to determine instabilities. Each one is tested on real data obtained in the machining of Waspalloy, Haynes 282 and Inconel 718. Experimental data, in both Conventional and High Pressure Coolant (*HPC*) environments, are set in four different states depending on materials grain size and Hardness (*LGA*, *LGS*, *SGA*, and *SGS*). Results reveal that PCA method is useful for visualization of the process and detection of anomalies in online processes.**

Keywords—Stability detection, Radial turning, PCA.

I. Introduction

The common use of planes engines, are growing the demand of materials with high mechanical resistance at high temperatures, what has incremented the development of superalloys. These materials are lighter and smaller than usually used alloys, what enable to reduce the fuel consume.

Superalloys are also able to support high temperatures and they have a high mechanical resistance, what fit them perfectly in the aerospace sector.

These materials usually need to be machined and due to their strength, they are considered as hard turning materials. In this case, a radial turning process is applied to three of the wide variety of superalloys that can be founded.

Radial turning is a machining process that removes material from the outer diameter of a rotating cylindrical alloy. The tool is moved linearly parallel to the rotation axis. Turning is a complex process which involves various physical phenomes such as plastic deformation, contact friction, etc. Hard turning refers to a material with high hardness, such as superalloys, which usually are heat treated before they are performed. These materials produced bigger wear and forces during the process due to their hardness.

Industries which work with radial turning processes have always been looking forward to production optimization. Improving the tool life is one of the usual topics in this area, what is obtained by reducing tool wear. Choudhury and Srinivas [7] and M. Murua [1] predicted tool wear using some regression models, while Tugrul and Yigit [8] used also neural networks for tool wear and surface roughness, which is another prediction topic in machining processes. Tool wear also depends on the alloy hardness, cutting parameters as Sardinas [6], Sahu [3] and Bonilla exposed on their articles, the cooling conditions [4], where A.Suarez concludes that HPC produces less wear than conventional lubrication, grain size [5] [2], where Olovsjo demonstrate notch wear predominance for materials with large grains (LG) against materials with small grain (SG). Kumar [13] optimize a multi-objective process for laser cutting process of superalloys using PCA method.

Parameters exposed, also affect to the cutting forces and the final quality. According to the forces, R.S.Pawade [16] demonstrates that larger cutting forces generated poor surface finish and extensive surface damage and Cedergren [17] deduce the importance of considering work material microstructure when studying cutting forces. In this paper, stability is used as a basic parameter to improve radial turning processes with experimental data.

II. Experimental Analysis

In this paper a study of the stability of a radial turning process for superalloys is done. This process is based on the forces that the ceramic tool supports during the turning against three different superalloys. All of them are Nickel-based superalloys, which differ from the others in the rest of the chemical components. These superalloys are Inconel 718, Waspalloy and Haynes.

Mentioned materials can be found in wide variety states, which are set by thermal heating and cooling processes such as annealing, which is used in this study. Annealing is a process that induces microstructural changes such as recrystallization and grain growth [11]. An alloy treated at high temperature and for big annealing periods, modifies the structure causing a recrystallization. Grain growth can also be obtained by heat treatment. This is achieved by controlling the times of heating and cooling.

Depending on the grain size, two states have been obtained for this study, which are called Large Grain (LG) and Small Grain (SG). In Fig.1 it can be shown the difference between these two states. In terms of strength, Aged (A) and Solutioned (S) are differentiated, where Aged is called to the stronger one.

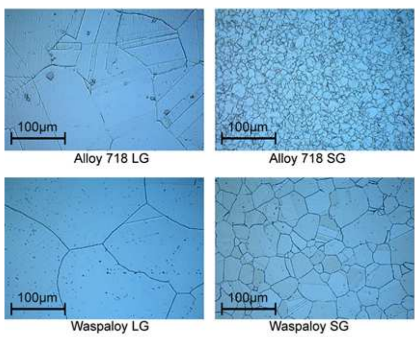

Fig. 1. Difference between LG and SG.

Superalloys are also lubricated to reduce the high temperature and forces generated during the machining process. In this case, conventional lubrication of 6 bar and High Pressure Coolant (HPC) of 80 bar are chosen to achieve that temperature reduction. In radial turning processes, test is called to a determined number of passes through the workpiece. A transition of the tool from the surface of the superalloy until the center of it is considered as a pass.

A test is made by an accumulation of passes and on each material the number of passes is not the same. In the case of Inconel 718 and Waspalloy, 6 passes are done to complete a test, while 4 passes are needed for Haynes. In the Table I, is shown the number of test measured for each superalloy.

TABLE I. NUMBER OF TESTS

		SGS	SGA	LGS	LGA
Inconel	***Conventional***	2	3	3	2
	HPC	X	3	X	2
Haynes	***Conventional***	X	X	2	2
	HPC	X	X	1	1
Waspalloy	***Conventional***	2	2	1	2
	HPC	1	2	1	2

Other parameters are also set on this study. These parameters are the same for every material during the experiments: entering angle (91º), rake angle (0º), inclination angle (0º), nose radius (0.4 mm), cutting speed (30 m/min), feed rate (0.1 mm/rev) and cutting depth (2 mm).

While one of the passes is running, the force between the tool and the superalloy is measured, which is called F. Resulting cutting force breaks down into 3 components called Fx, Fy, Fz (see figure 3) and this forces are measured using sensors, which are perpendicular each other. Fy force, has the direction of the cutting speed, Fx is in the radial direction and Fz is the orthogonal direction. When a pass is finished, 2 different tool wear are also measured, Flank wear and Notch wear. The Notch wear consist on the wear that appears where the tool and the superalloy are in contact. However, Flank wear is measured in 9 different points into the tool just after the Notch one. In Fig.2 is shown how the tool seems when a pass is made.

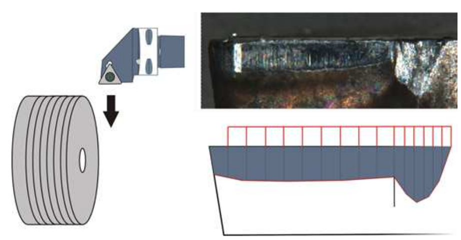

Fig. 2. Wear measurement.

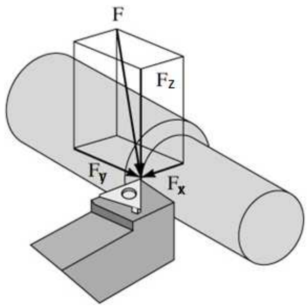

Fig. 3. Force components.

In Fig.4, forces from the 3 components are represented. These signals are a particular example taken from one pass, but in general, the signals obtained due to any of the passes has the same appearance. In this paper, force signals where analyzed to obtain the stability for each superalloy on each state and lubrication.

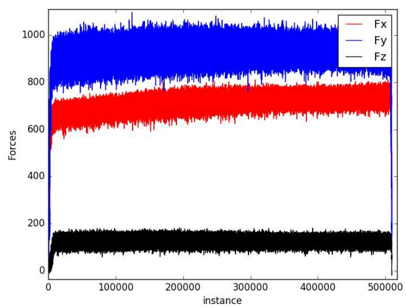

Fig. 4. Measured forces for a pass in the 3 components.

III. Experimentation

In this section the experimentation done is exposed, which is based on the forces and achieves to classify instability for every state. Before anything else, a filter to the force signal is done, where the initial and the final part of the signal are deleted. This filter is made to remove the warm-up and the stop of the process, which are not going to appear in the real machining processes. In figure 5, the filtered signal is shown.

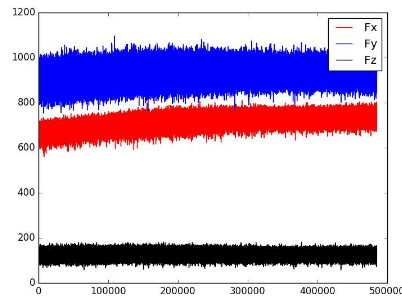

Fig. 5. Filtered forces for a pass in the 3 components

Two different methods are exposed. On one side, the first pass of every test stability is studied. Each force component is studied independently and then mixed. A robust three-sigma edit rule is used, which was proposed by Maronna [9]. This test is applicate following the next steps. Firstly median of each force is calculated, which is the center value of the sorted data Me_x; Me_y; Me_z. Next step is to calculate a vector of the standard deviation from the median.

$$|F_{xi}-M_{ex}|=V_x \quad (1)$$

$$|F_{yi}-M_{ey}|=V_y \quad (2)$$

$$|F_{zi}-M_{ez}|=V_z \quad (3)$$

Where F_{zi} is the i^{th} value of the force in component z. Median is extracted from those vectors and divided by 0.6745.

$$MADN_X = \mathrm{Median}(|F_{xi}-M_{ex}|)/0.6745 \quad (4)$$

$$MADN_Y = \mathrm{Median}(|F_{yi}-M_{ey}|)/0.6745 \quad (5)$$

$$MADN_Z = \mathrm{Median}(|F_{zi}-M_{ez}|)/0.6745 \quad (6)$$

Finally, a quantitative value is obtained to classify the stability, which is the value of dividing the maximum of (1) with (2).

$$P_x = \mathrm{Max}(|F_{xi}-M_{ex}|)/\ MADN_X \quad (7)$$

$$P_y = \mathrm{Max}(|F_{yi} - M_{ey}|) / MADN_Y \quad (8)$$

$$P_z = \mathrm{Max}(|F_{zi} - M_{ez}|) / MADN_Z \quad (9)$$

P_x, P_y, P_z are then limited by an expert to expose when is considerable stable and when is unstable.

On the other side, the stability of the first pass is analyzed while the machining process is running. This achieve is obtained in three steps. Firstly, a statistic technique (PCA) is used to reduce the dimension from the 3 force component to only two of them, so that it can be seen easily. PCA is based on combining input components to obtain new ones (C_1; C2) that are linearly independent between them and maintain as much original information as possible. This technique is used many times in the literature due to its easy way of programming. Some of the applications of this technique are to achieve objectives such as surface roughness [14], structural damage diagnosis[15], multi-objective optimization [13].

In this case PCA is applied to the first pass of the test to obtain a dimensional reduce which enable to represent the variables into a graphic, from 3 components (Fx, Fy, Fz) to 2 new axis(C_1; C2). After representing data into the new axis the centroid of the pass is calculated.

$$O_1 = \sum C_1 i / N \quad (10)$$

$$O_2 = \sum C_2 i / N \quad (11)$$

Where O_1 and O_2 are the values of each axis of the centroid. After that, other passes are represented on the same principal components, so the progress of the test can be seen graphically. Instead of classifying graphically, a quantitative measure is calculated, which is the maximum distance from any of that pass point to the centroid of the first pass.

$$D = \mathrm{Max}(\sqrt{((C_{1i} - O_1)^2 + (C_{2i} - O_2)^2)}) \quad (12)$$

These distances are represented for each test, what would provide the progression of this value during the machining process. A test is considered unstable if the distance for any of the passes is 200% times the value obtained for the first pass.

IV. RESULTS

As it was mentioned in section III, the first step is to filter the signal. Initial and final parts are removed. Figure 5 shows how the signal remains after removing those parts. This filter had gone through the signals of the study, which had been used after the filtering process for the rest of the methods.

Results are exposed only for a few tests which are classified as stable and unstable. This tests are Waspalloy SGS Conventional as unstable and Haynes LGA HPC as stable. In figure 6 and figure 7 this tests first pass is shown.

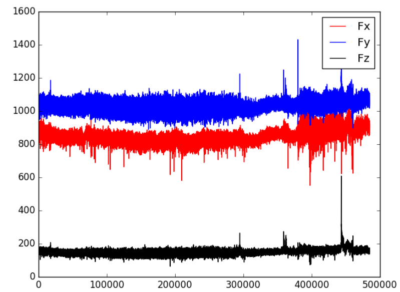

Fig. 6. First pass of Waspalloy SGS Conventional.

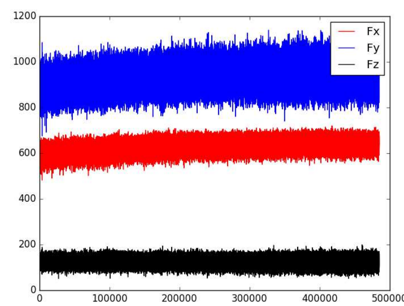

Fig. 7. First pass of Haynes LGA HPC.

A. *Stability by force*

In this section, classification for the first pass of the test is obtained. To achieve it, some quantitative values have been taken from each of the force component (F_x, F_y, F_z). Chosen variables are the median of the filtered force, maximum distance between mentioned median and measured forces and the median value of all the distance measured. 3 values are calculated for each force component. From all the values obtained for each pass, a combination of them is made for getting a quantitative value, which classifies the tests.

The measure chosen is the mean value of the 3 components called *force proportion*, which is referred to the maximum distance value divided by the median distance value. This quantitative measure classifies between stable and unstable tests, where stable will be when a low value appeared an unstable when a great value is obtained. In this case, 7.33 is obtained for Haynes LGA HPC and 26.52 for Waspalloy SGS Conventional.

This results obtained confirms the hypothesis of detecting instability with the force. Validation of this method should be obtained by testing with more data. This process can also be used into the rest of the passes of each test, what could provide a good reference to determine when to stop the machining process. The main problem of this method is that this method is not able to be used into online processes. This objective is solved by using the method exposed in IV-B.

B. Stability in function of the first pass

In this section the stability of the test is studied based on its first pass. Principal Component Analysis (PCA) is applied to the first test and the centroid of the result is obtained before overloaping the rest of the passes PCA. PCA analysis has been realized to reduce until a 2 dimensions, so that the result can be graphically exposed.

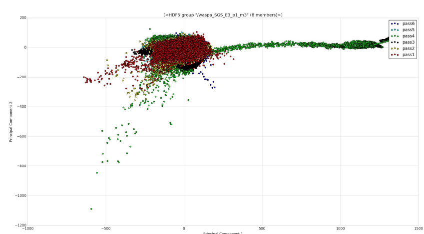

Fig. 8. Waspalloy SGS Conventional 6 passes.

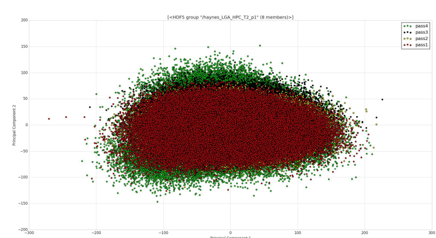

Fig. 9. Haynes LGA HPC 4 passes.

Figure 8 and figure 9 shows the PCA for both cases of Waspalloy and Haynes respectively. In both graphics, the full test in shown, where each of the passes has a different color to be appreciated. Fixing on Figure 8 and figure 9 it will be possible to classify each test easily. Note that 4th pass of Waspalloy is gone far through the first principal component, while Haynes remains in the same space every pass. Instead of doing it graphically, a quantitative measure is calculated. Measured value consists in the maximum distance measured for each pass to the centroid of the first pass. This measure can also be obtained online when the centroid is calculated. A very useful system can be obtained with this method to detect anomalies while the process is running. When a test distance increase heavily, it will be considered that this test is instable. In figure 10 and figure 11, the maximum distance for each pass is represented.

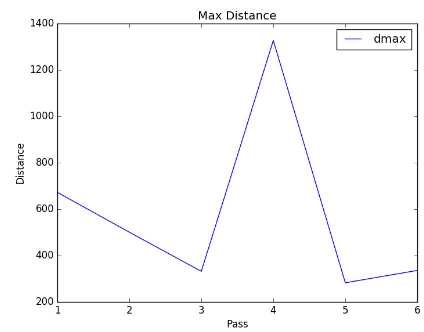

Fig. 10. Maximum distance to the centroid of the first pass for each pass in Waspalloy SGS Conventional.

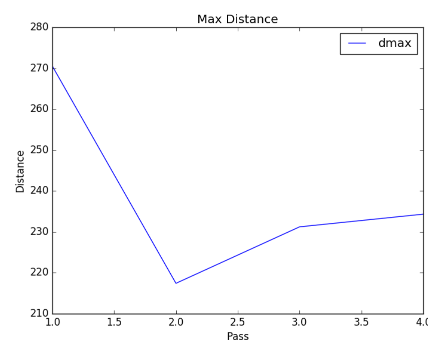

Fig. 11. Maximum distance to the centroid of the first pass for each pass in Haynes LGA HPC.

It can be seen that in this case, Waspalloy has distances between 600 and 800 while Haynes has no measure bigger than 300. This result confirms the theory of the stability for Haynes

LGA HPC test and instability for Waspalloy SGS Conventional.

V. Conclusions and Future Works

Development of stability detection models for machining processes using forces is a difficult task due to all the factors that have impact on the force measured. In this paper, two different models have been exposed:

On the first method, the median values are calculated, what means that a range of data is needed to do it, what makes it an offline method. This method has been used only for the first pass but it can be also useful for all the passes of each test, providing a stability test when a pass is finished.

On the other method, an intuitive 2 dimension representation of forces is done, what makes easier to understand the relationship between forces in different components. The main problem of this method is that it is supposed that the first pass of each test is stable, what means that if the first pass is instable, this test is not right to use.

That reason makes the development of a new method necessary, which could be a combination between both explained methods in terms of detecting stability. This will consist in the use of the first method to detect the stability of the first pass and when this stability is confirmed, apply the second method online in order to find any instability that would activate an alarm to stop the machining process. This machining process can not be stopped in any point, it is necessary to maintain machining until a specific point where stopping the process do not mean breaking the material.

In this study, two methods had been applied to two different tests that where classified previously. In order to validate these algorithms, more tests should be used, what would be done in future work when the rest of the tests are classified as stable or instable.

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5.1.3. Instability detection on a radial turning process for superalloys.

- **Title**: Instability detection on a radial turning process for superalloys.
- **Authors**: Alberto Jiménez Cortadi, Itziar Irigoien, Fernando Boto, Germán Rodriguez, Asier Gonzalez Gonzalez
- **Book of Proceedings**: International Joint Conference SOCO'17-CISIS'17-ICEUTE'17 León, Spain, September 6–8, 2017, Proceeding
- **Publisher**: Springer
- **Year**: 2017

Two different models for instability detection in a radial turning process are proposed in order to prevent fault appearance. This methods allows to detect instability on this machining process based on the forces. Median Absolute Deviation Normalized (MADN) and Principal Component Analysis (PCA) are the statistical methods used to classify those tests. The results have showed that the models are close to expert classification of the tests stability.

Instability detection on a radial turning process for superalloys.

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Abstract. Two different models for instability detection in a radial turning process are proposed in order to prevent fault appearance. This methods allows to detect instability on this machining process based on the forces. *Median Absolute Deviation Normalized* (MADN) and *Principal Component Analysis* (PCA) are the statistical methods used to classify those tests. The results have showed that the models are close to expert classification of the tests stability.

Keywords – Radial turning, Fault detection, Instability detection, MADN, PCA.

1 Introduction

Industry 4.0 symbolizes the fourth generation of industrial activity as a result of the fourth industrial revolution generated by the development of intelligent systems and internet-based solutions [1]. This industrial revolution is based on the evolution of information and communication technologies (ICT) and the new possibilities of data analytics developed in terms of Big Data. Industry 4.0 can be applied in many topics such as Planning & logistics, predictive maintenance, etc.

Condition based monitoring (CBM) is a maintenance program, based on the data collected by condition monitoring, which recommends maintenance actions. Diagnostics and prognostics are two important aspects in maintenance. Diagnostics deals with fault detection, which is a task to indicate whether something is going wrong in the monitored system [2]. Prognosis deals with fault prediction before it occurs. The estimation of the remaining useful life constitutes one basis example of prognosis. It is an important task to know if the process is to maintain its functions over time [3].

In the case studied in this paper the fault detection is the main goal due to its direct relation with the tool wear. Actually a preventive maintenance is being used in the machining process, which is pretended to be changed into a condition based monitoring in order to inprove tool life and increase the benefits.

Since its first application in te automotive sector, aerospace industries and military, condition based monitoring has proved to be an efficient maintenance policy from economic and safety points of view [4].

Industries, specially the ones which work with radial turning processes, have always been looking forward to production optimization. Improving the tool life is one of the main topics in this area, what is obtained by reducing tool wear. Zhang developed a flank wear model using the distribution of the cutting forces [5]. Tuğrul and Yiğit [6] have predicted tool wear and surface roughness using neural networks, which is another common topic in machining processes. Tool wear also depends on the alloy hardness, vibration amplitude [7], cutting parameters [8], grain size [9] and the cooling conditions [10]. These also affects to the cutting forces and the final quality. According to the forces, it is necesary to maintain a stability to keep the linearity on the wear measure [11] and to prevent faults [12] [13] [14] [15]. This paper shows some methods to achieve the objective of preventing fault appearances in terms of the forces applied.

This paper has the following structure. The Industrial application is explained in Section 2. Section 3 exposes the two differents methods used to detect instabilities on the process and the results of those methods are shown in Section 4. Finally, section 5 offers conclusion remarks.

2 Industrial Application

A radial turning process in nickel based superalloys is studied in order to determine the stability of these materials. This process is based on the forces that the ceramic tool bears during the turning. Even if all the materials are Nickel-based superalloys, they differ from the others in the rest of the chemical components. These superalloys are *Waspalloy*, *Inconel 718* and *Haynes*.

Mentioned superalloys can be found in a wide variety states, which are set by thermal heating and cooling processes such as annealing, what is applied on this study. Annealing is a process that induces microestructural changes such as recrystallization and grain growth [16]. Alloys treated at high temperature and for big annealing periods, causes a break on the crystallization structure, which will recrystallize in another way when the temperature goes down. While grain growth can also be obtained by heat treatment, the process of reducing the grain size is not possible to be obtained by this process. These recrystallization and grain growth processes are achieved by controlling the times of heating and cooling.

According to the grain size, two states can be distinguished on this study, which are called *Large Grain*(LG) and *Small Grain* (SG). In Figure 1 it can be shown the difference between this two states. In terms of strength, *Aged*(A) and *Solutioned*(S) are differentiated, where Aged is called to the stronger one.

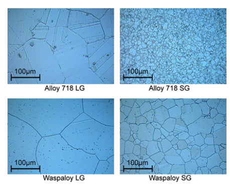

Fig. 1. Difference between *LG* and *SG*

Turning process is also lubricated to reduce the high temperature and high forces generated during the machining process. In this case, *conventional lubrication* of *6 bar* and *High Pressure Coolant* (HPC) of *80 bar* are chosen to achieve that temperature reduction. In radial turning processes, test is called to a determined number of passes through a workpiece. A pass is considered finished when the tool arrives from the surface of the superalloy until the center of it. A test is made by an accumulation of passes which is not the same for each material. In the case of *Inconel 718* and *Waspalloy*, 6 are the passes done to complete a test, while 4 passes are needed for *Haynes*. In Table 1 is shown the number of test measured for each superalloy.

		SGS	SGA	LGS	LGA
Inconel	Conventional	2	2	2	2
	HPC	x	3	x	2
Haynes	Conventional	x	x	2	2
	HPC	x	x	1	1
Waspalloy	Conventional	2	2	1	1
	HPC	1	1	1	1

Table 1. Number of tests.

Some other initial conditions are also set up on this study. This conditions are the same for all of them.

While one of the passes is running, the force between the tool and the superalloy is measured. This force is then descomposed into 3 components called *Fx, Fy, Fz*(see Figure 2), which are perpendicular to each other. Once a pass is finished, tool wear is also measured, which is measured in two different ways: *Flank wear* and *Notch wear*. *Flank wear* is measured in 9 different points into the tool where tool and the superalloy are in contact. *Notch wear*, which is not used on this study, consist on the wear that appears just after the *Flank wear* and is usually bigger. In Figure 3 is shown how the tool looks like when a pass is made.

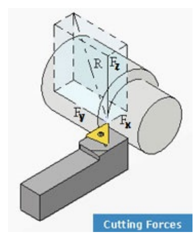

Fig. 2. Force components

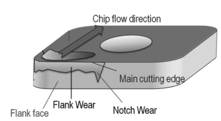

Fig. 3. Wear measurement.

In Figure 4, the 3 force components are represented. These signals are a particular example taken from one pass, but in general, the signals obtained along any of the passes has similar appearance. In this paper, force signals are analyzed to obtain the stability for each superalloy on each state and lubrication.

Finally, beside all experimental data gathered, an expert opinion has been used in order to determine the stability for the first pass of each test and the complete test.

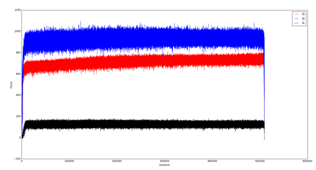

Fig. 4. Measured forces for a pass in the 3 components.

3 Methodology

This section explaines the processes applied in order to achieve the goals exposed before. This experimentation is based on the forces between tool and material for instability detection and those forces and the set up conditions for the rest of the studies.

3.1 Instability Detection

Instability detection is an important issue since it is directly related to the tool wear linearity. An unstable process will produce an unlinear tool wear, which is a fault on the process. To detect instability, forces measured between tool and material are used. This forces are shown in Figure 4.

Two different points of view are exposed. On the one side, the stability of each pass of every test is studied independently. A robust three-sigma edit rule is used, which was proposed by Maronna [17]. On the other side, the stability of the full test is analyzed while the machining process is running. This end is obtained comparing the actual pass with the first pass, which has been previously identified as stable or not. Some quantitative values are obtained in order to determine this instability.

MADN method This method provides a model to detect instabilities from a specific pass of a test. Application of this method has been made in three steps. First median value of each force component (shown in Figure 2) is obtained, which is the center value of the sorted data values $Me_i = Median(F_i)$, where $i = x, y, z$ is the force component. Second the absolute standard deviations are calculated from the median for each force component:

$$|F_{i,j} - Me_i| \tag{1}$$

Where F_{ij} is the jth value of the force in component i. Median value of this deviation is then divided by 0.6745 [17].

$$MADNi = \frac{Median(|F_{ij} - Me_i|)}{0.6745} \tag{2}$$

The robust three-sigma edit rule (see Maronna [17]) establishes that an observation F_{ij} is outlier for F_i if:

$$\frac{Max(|F_{ij} - Me_i|)}{MADNi} > T \tag{3}$$

In the case studied here, a test will be considered instable if at least 2 of the 3 components are instable. Different threshold values are explored in order to find the best value in this particular process. This approximation is validated by a confusion matrix, (Table 2).

	Real class	
Pred. class	Stable	Unstable
Stable	T_p	F_p
Unstable	F_n	T_n

Table 2. Confusion matrix in a classification problem.

where first row correspond to the stable predicted value and first column to the stable classification of the expert. Accuracy is a percentage value that presents the approximation between predicted value and forehand classification.

$$Accuracy = \frac{T_p + T_n}{T_p + T_n + F_p + F_n} \tag{4}$$

The threshold with bigger Accuracy will be considerated as the optimum value to classify the instability on this process.

PCA visualization method In this section, a method for analizying stability of a whole test is presented. This method is based on the comparison with the first pass of the signal while the machining process is running. This end is achieved in three steps. First, a classical statistical technique (Principal Component Analisys, PCA) [18] is applied in order to reduce the dimension from the 3 force components to only two dimensions, so that the full signal can be visualized easily. PCA is based on combining linearly input features, in this case the force components of the first pass $(F_{ct}(1),\ t = 1, \ldots, T;\ c = x, y, z)$ to obtain new ones $(C_k(1),\ k = 1, 2)$ that are linearly independent between them and maintain as much of the original information as possible.

Second, subsequent passes are projected on the same space, so the progress of the test can be seen graphically. In addition to graphical classification, a quantitative measure is calculated: given $F_t(p) = (F_{xt}(p), F_{yt}(p), F_{zt}(p))$, the maximum distance from any time point t of this pass p to the centroid of the first pass is:

$$D(p) = \max_{t,\dots,T} \sqrt{\sum_c (F_{c,t}(p) - \overline{F_c(1)})^2}. \tag{5}$$

These distances are represented for each test, what would provide the progression of this value during the machining process. One test will be considered as unstable when a value $D(p)$ is twice the value $D(1)$ corresponding to the first pass.

Validation of this model is made comparing stability classification obtained with the one offered by the expert. To achieve this, confusion matrix is calculated an accuracy value is obtained.

4 Results

4.1 Instability Detection

In this section, the results obtained for achieving instability classification are exposed. The methods explained above are applied with two different objectives: Method MADN is used for classifying a pass of the test and PCA method is applied to detect which test is considered as stable and which one as unstable.

MADN method This method provides a classification for only one pass of each test. As it was mentioned on the methodology section, a threshold value has been searched in order to determine the optimum value for this specific process. Stability results obtained for each first pass of every test is compared with an expert opinion. Accuracy values for some of the test are shown in Table 3:

Threshold	Accuracy
3	0.28
5	0.28
7	0.72
8	0.82
10	0.79

Table 3. Accuracy value for different thresholds.

The results obtained shows that a particular threshold is required for this case. This process is used on the first pass of the test but it can also be used for the rest of them with the goal of validating the threshold value.

PCA visualization method In this section the stability of the test is studied based on the first pass. Principal Component analysis (PCA) is applied to measured forces to obtain a 2 dimension visualization. In Fig. 5 a PCA analysis can be seen, which is realized to achieve the objective of detecting instability for online machining processes. A test is considered as unstable when a particular value of any pass is over 2 times the maximum distance of the first pass:

$$D(p) > 2 * D(1) \tag{6}$$

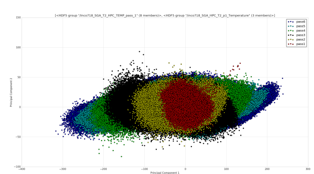

Fig. 5. Principal Component analysis of a full test.

In Figure 6 maximum distance measured for all the test is represented. In this case it can be seen that it is classified as stable test. This proceding is made for the rest of the tests and the results obtained are exposed in the Table 4.

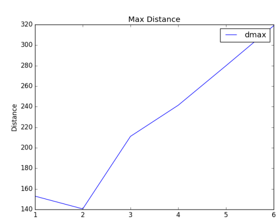

Fig. 6. Maximum distance to the centroid of the first pass for each pass.

	Stable	Instable
Stable	13	5
Instable	2	9

Table 4. Confusion matrix.

Most of the test are correctly classified, what provides a 76% of the accuracy.

5 Conclusions

Stability detection models for machining processes using forces is a difficult task due to all the factors that have impact on the force measured. In this paper, two different models have been exposed:

The MADN method,is an offline method. This method can be used not only for the first pass but also for all the passes of each test, providing a stability test when a pass is finished. This method provides a value of stability during the process not having to stop the turning after each pass for wear measurement instead of an instability is detected, what enables to reduce machining time.

PCA visualization method, provides an intuitive 2 dimension representation of forces, what makes easier to understand the relationship between forces in different components. This method supposes that the first pass of each test is stable, what means that if the first pass is instable, this test could bring a stability result that will not be according to the reality. This method could also be applied online, what would provide a fault detection method without needing to stop the turning process.

This two methods are useful to change the actual preventive maintenance into a predictive maintenance, what enable to detect an instability before it occurs.

In future work it will be studied the prediction of the wear measure in the tool when the test is considered stable in order to achieve a predictive maintenance in this process.

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5.2. Estimación de RUL en máquina herramienta.

5.2.1. Predictive Maintenance on the Machining Process and Machine Tool.

- **Titulo**: Predictive Maintenance on the Machining Process and Machine Tool.
- **Autores**: Alberto Jimenez-Cortadi, Itziar Irigoien, Fernando Boto, Basilio Sierra, German Rodriguez
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This paper presents the process required to implement a data driven Predictive Maintenance (PdM) not only in the machine decision making, but also in data acquisition and processing. A short review of the different approaches and techniques in maintenance is given. The main contribution of this paper is a solution for the predictive maintenance problem in a real machining process. Several steps are needed to reach the solution, which are carefully explained. The obtained results show that the Preventive Maintenance (PM), which was carried out in a real machining process, could be changed into a PdM approach. A decision making application was developed to provide a visual analysis of the Remaining Useful Life (RUL) of the machining tool. This work is a proof of concept of the methodology presented in one process, but replicable for most of the process for serial productions of pieces.

Predictive Maintenance on the Machining Process and Machine Tool

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Abstract

This paper presents the process required to implement a data driven Predictive Maintenance (PdM) not only in the machine decision making, but also in data acquisition and processing. A short review of the different approaches and techniques in maintenance is given. The main contribution of this paper is a solution for the predictive maintenance problem in a real machining process. Several steps are needed to reach the solution, which are carefully explained. The obtained results show that the Preventive Maintenance (PM), which was carried out in a real machining process, could be changed into a PdM approach. A decision making application was developed to provide a visual analysis of the Remaining Useful Life (RUL) of the machining tool. This work is a proof of concept of the methodology presented in one process, but replicable for most of the process for serial productions of pieces.

Keywords: PdM, RUL, machining process, concept drift, real application

1. Introduction

The Oxford Dictionary (2015) defines maintenance as: "the process of preserving a condition or situation or the state of being preserved". Maintenance is applied mostly to everything, not only in manufacturing processes

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[1], but also to railways, bikes, cars, computers, etc. Its importance has increased recently while enterprises have noticed the value and cost reduction it implies. In the industrial sector, maintenance has the aim of maintaining a process's functions over time [2].

At the beginning of the industrial revolution, workers were responsible for equipment maintenance. As the complexity of the machines grew and the maintenance operations increased, enterprises started to include maintenance departments in their business plans. The concept of reliability appeared at the beginning of the 20^{th} Century when maintenance began to be concerned not only with solving failures, but also preventing them. With the arrival of computer science, maintenance strategies had another opportunity to develop more complex models.

Since those beginnings, computational and data analysis technologies have evolved. Not all maintenance methods work for all the processes and assets, but the ones that have been useful have been adapted for new purposes. Currently, the specific needs of each company determine the most appropriate way of performing maintenance to optimize its resources.

Maintenance can be divided into three main types: corrective, preventive, and predictive maintenance. The next paragraphs will describe each of them.

1.1. Corrective Maintenance

This type of maintenance is based on solving the faults that have already happened, which implies it only takes place when the process or machine has a critical halt [3]. Usually, this maintenance provokes a production stop, involving a reduction of production and an increase in costs. The repair time cannot be predicted, nor the degradation or generation of other failures associated with other parts of the process [4]. Because of this, corrective maintenance is used in processes where failures do not have a critical impact on the production.

1.2. Preventive Maintenance

Preventive Maintenance (PM) is a schedule of planned maintenance actions aimed at the prevention of spontaneous breakdowns and failures. It is based on periodic reviews of the system with the aim of preventing failures of it. Despite corrective maintenance, this maintenance is usually applied outside the production time. The objective of this type of employed maintenance is to reduce the number of corrective maintenance actions applied through periodic checks and replacement of worn parts. Ashayeri [5] presented a computer aided planning system for the maintenance of a set of high precision CNC machining centers. Coro et al. [6] presented scheduling inspection of gas turbine welded structures, based on reliability calculations and overhaul findings.

This is demanding maintenance, requiring strict supervision and development of a plan that must be carried out by qualified personnel. In addition, if it is not correctly applied, there will be a breakdown, which provokes a cost in productivity [7].

1.3. Predictive Maintenance

Predictive Maintenance (PdM) is a maintenance type that occurs before breakdown happens. It is based on precise formulas in addition to sensor measurements, and maintenance is performed with the analysis of the measured parameters. The premise of this maintenance is to ensure the maximum interval between repairs and to minimize the cost and number of scheduled maintenance operations (Mobley [8]).

A predictive maintenance program consists of three steps (see Figure 1):

- Data acquisition.
- Data processing.
- Machine decision making.

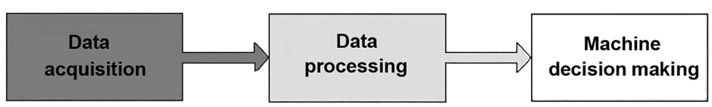

Figure 1: Steps followed to develop a predictive maintenance.

Although there are monitoring systems dedicated to predicting errors in industrial processes such as Manco et al. [9] exposed for metro doors, the techniques of data analysis and automatic learning have not yet been exploited completely. In this article, some of these techniques will be applied to develop a predictive maintenance. The obtained results will be shown with data extracted from a real process in production. Anticipating how much time is allowed before a failure occurs, which is commonly called the

Remaining Useful Life (RUL), is an important task due to the important costs associated with the early replacement of tools [10]. Results show that RUL prediction provides a better accuracy and enables each tool to machine more pieces. Furthermore, the RUL algorithm developed has been deployed with a user visual interface for industrial maintenance purposes, achieving good results also in terms of generalization for other processes. The methodology in this use case is replicable in most of the processes with a serial production of pieces where the machining tool is changed with a certain frequency. Therefore, in this kind of process, the current preventive strategy can be changed by a predictive strategy where the number of pieces for the next tool substitution is predicted.

Section 2 describes the data acquisition step. Section 3 exposes some preprocessing methods. Section 4 presents the machine decision making, where diagnostics and prognostics are explained. Section 5 exposes the particular problem and the developed methodology. Finally, Section 6 concludes about the results and exposes some future works.

2. Data Acquisition

The acquisition of data is the process of collecting and storing data from a physical process in a system, which is essential for the implementation of a predictive maintenance. The data collected in a predictive maintenance program can be classified into two main types: event data and condition monitoring data. While the event data include information about what happened to the asset and which maintenance was applied to it, the condition monitoring data are related to the measurements of the health of the physical asset.Modoni et al. [11] developed a framework for information notification among manufacturing resources. There is a huge variety of signals such as vibrations, acoustics, oil analysis, temperature, pressure, humidity, and climate. In order to collect these data, many sensors have been developed such as ultrasonic sensors, accelerometers, gyroscopes, rain sensors, etc. Many industries are working on improving sensor technologies and computers, which implies an easier way for storing data (Wu et al. [12]).

3. Data Processing

Acquired data are susceptible to presenting some missing, inconsistent, and noise values. Data quality has a great impact on the results obtained by data mining techniques. To improve these results, preprocessing methodologies can be applied. Data preprocessing is one of the most critical steps, which deals with the preparation and transformation of the initial dataset. Data preprocessing methods can be divided into three main categories:

- Data cleaning.
- Data transformation.
- Data reduction.

3.1. Data Cleaning

Raw data are usually incomplete, noisy, or inconsistent, especially event data, which are manually entered. Errors in data may be caused by many factors including human factors to sensor faults, and detecting and removing those errors improve data quality [13]. Dirty data can cause confusion for the mining procedure, and in general, there is no simple way of cleaning. Some techniques are based on human inspection, which usually is helped by some graphical tool. Mean or median values are typically used to pad unknown values with zeros. More sophisticated methods such as regression techniques can be used to estimate missing values. Wei et al. [14] compared eight different methods to recover missing data for mass spectrometry based metabolomics data (zero, half minimum, mean, median, random forest, singular value decomposition, KNN, and QRILC (Quantile Regression Imputation of Left Censored data)). In addition to missing data, noisy values are also a problem for data clearance. The work presented by Libralon et al. [15] proposed the use of clustering methods for noise detection. Data outliers can also be detected by clustering techniques, where similar values are organized into groups. Values that are set outside the clusters will be considered as outliers. Jin et al. [16] applied a one class SVM method for detecting change points in time series data, which would imply a degradation in the system. Maronna et al. [17] proposed another method called the three-sigma edit rule, which was used in Jimenez Cortadi et al. [18] for outlier detection on a radial turning process.

3.2. Data Transformation

Data transformation has the aim of obtaining a more appropriate form of the data for one step further in modeling. Transformations can include standardization, where data are scaled to a small range and make different signals comparable. Smoothing is also applied to data to separate the signal and the noise. For a given dataset, smoothers can be divided as forward and/or backward looking. We will only consider backward looking smoothers, which replace any given observation by a combination of observations at and before it. A short overview of different smoothing methods can be found in [19]. Yahyaoui and Al-Daihani [20] suggested a novel Symbolic Aggregate approXimation (SAX) and compared it to the standards, obtaining better results for time series classification. Smoothing techniques also include regressions and clustering.

3.3. Data Reduction

Having a considerable amount of data can be an issue for machine decision making in terms of having a big computational cost. As the number of data increases, the time spent by the hardware will also increase. To maintain the computational cost while the amount of data is sufficient, some methodologies have been developed over the years. The best known one is principal component analysis (Jolliffe and Cadima [21]). This method is based on combining input features linearly to obtain new ones, which are linearly independent of each other and maintain as much of the original information as possible.

Other data reduction methods are recursive feature elimination [22] and *t*-distributed Stochastic Neighbor Embedding (t-SNE) applied by Pouyet et al. [23] to provide a non-linear representation of spectral features in a lower 2D space. More feature selection techniques were presented in Guyon and Elisseeff [24]. Wang et al. [25] proposed a dimensionality reduction method using global characteristics such as seasonality, trend, periodicity, and skew for feature selection before using a Self-Organization Map (SOM).

4. Machine Decision Making

This is the last step in the maintenance decision, which can be divided into two main categories: diagnostics and prognostics. Diagnostics focuses on detection, identification, and isolation of faults when they occur, while prognostics pretends to predict failures before they happen and is related to predictive maintenance. Diagnostics and prognostics are complementary in that diagnostics adds new information from the process. This information enables going from an unsupervised problem to a supervised one. A supervised model is always easier to develop and has greater accuracy, which implies a better prognostics model.

4.1. Diagnostics

Fault diagnosis is the process of tracing a fault by identifying its symptoms, applying knowledge, and analyzing test results [26]. Accurate diagnosis consists of detection of the faults and determination and estimation of the size and nature of the location. Fault diagnosis requires advanced algorithms such as Machine Learning (ML) techniques, which are increasingly applied in not only the industrial sector, such as manufacturing, aerospace, and automotive, but also in business, finance, and science. The most frequently employed algorithms in the industrial sector are: linear regression, random forest (Mattes et al. [27]), Markov models (Cartella et al. [28]), artificial neural networks (Farokhzad et al. [29], Kanawaday and Sane [30], Li et al. [31]), and support vector machines (Tyagi [32], Widodo and Yang [33]). Diez-Olivan et al. [34] provided an overview of the algorithms employed in the industrial sector for diagnosis.

These techniques can also be applied to detect changes in the system behavior as an indication of the beginning of malfunctions, which is called concept drift (Tsymbal [35]). Winkler et al. [36] applied a sliding window symbolic regression model for concept drift detection in dynamic systems. Klinkenberg and Joachims [37] detected concept drift by applying SVM and adjusting the window size to minimize the estimated generalization error. Zhukov et al. [38] detected concept drift on publicly available benchmark datasets with the random forest technique.

4.2. Prognostics

Predicting the time when a system or a component will no longer perform properly is referred to as prognostics (Galar and Kumar [26]). Prognostics predict future performance given the current machine status and past operation profile, which is an important task to know if the process will maintain its functions over time [2]. Two main prediction types can be found in machine prognostics: on the one hand, predicting RUL, which is explained in Section 1; on the other hand, predicting the probability that a machine has to keep on working without a failure up to some time [39]. Pham et al. [40] applied an ARMA model to vibration data for machine state forecast. Khelif et al. [41] used a Support Vector Regressor (SVR) to predict RUL. Djeziri et al. [42] provided a similar methodology to the one explained in this work where a fault prognosis was developed by a preprocessing method and an extrapolation of the previous values to predict RUL. Other examples in industry can also be found in [34].

5. Case Study

In this section, an application of predictive maintenance is exposed on a real machining process. The main goals of this study are to increase tool life and to identify whether there is a concept drift. These aims will be achieved applying some ML methods for RUL prediction and concept drift detection.

5.1. Industrial Process

The experiments were conducted on a CNC turning center with two tool posts, which could be moved on two axes independently with longitudinal and cross-feed movement. The cutting tool holder used was a C3-MTJNR-22040-16 equipped with a TNMG160408-PF insert for the external surface and a special tool holder equipped with a WNMG060408-PM insert for the inner diameter. During the machining process, the rotating revolutions were set to 1800 rpm. The current maintenance strategy applied was a very conservative method to change the machining tool when the specific number of pieces machined was higher than a threshold. Therefore, a predictive strategy was very interesting for this kind of processes.

5.2. Acquisition

During the turning process, from December 2017 until May 2019, several measurement were recorded, which provided information about how the machine was working. These Condition Monitoring (CM) signals were obtained with a 5Hz frequency. Although several signals were acquired, the final state of the tool (piece quality) was not measured. The acquired signals, such as spindle load, piece number, and tool position, were recorded as a collection of observations made sequentially through time, which are known as time series. In this case, experts in the process suggest the spindle load signal to be studied, while other signals are useful for segmentation and characterization. The spindle load represents machine effort and is the more critical signal over all the sensorized ones. As a result of this acquisition step, around 1100 series and 550,000 pieces were stored for further analysis. The technology applied for monitoring data is shown in Figure 2. The monitoring system (data recorder) was connected to the machine tool, which recorded a database accessible via the Internet and had different interfaces. The machine tool data recorder worked on the same principle as the black box on a flight deck. It communicated with the control unit of the machine and some independent sensors, in order to retrieve targeted data. The data recorder was able to communicate with Computer Numerical Control (CNC). Its design only permitted the recording device to communicate with the interface of the control unit, in order to access the control memory in read-only mode. At no point would it therefore disturb the execution of the program. All monitored data were configured by default to be stored in a secured remotely accessible database. The connection between the database and the machine tool data recorder was done through an Ethernet connection.

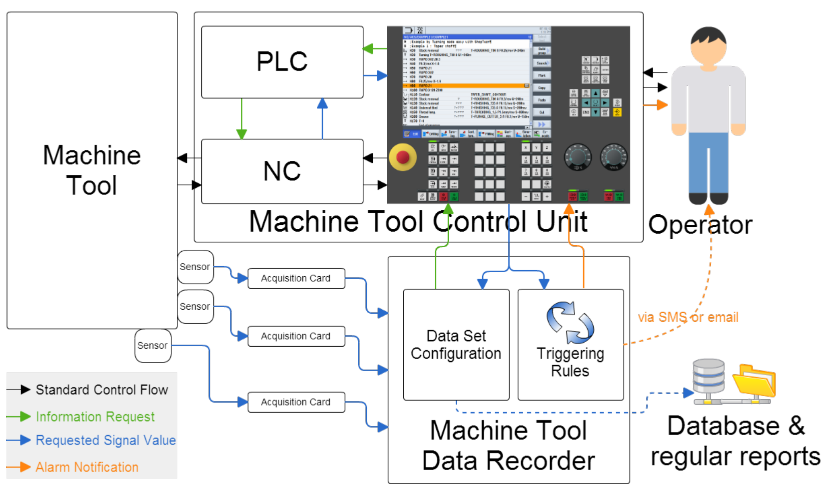

Figure 2: Data acquisition platform flows and architecture.

5.3. Data Processing

As explained before, there is a huge amount of possibilities, and in this work, reduction, cleaning, and transformation were applied.

Data reduction is based on extracting characteristics from the original signal to have a smaller amount of data, so the computational cost is reduced and the data are clearer. The first step is to cut the signal so that we can observe the spindle load evolution for each tool. To achieve this aim, the signal, which represents the number of pieces machined, was used, since the piece number is restarted when the tool changes. In addition to this reduction, each machined piece was characterized by the highest spindle load value recorded during its machined time, which was suggested by the expert.

The obtained characterization (see Figure 3) appeared to have some outliers, which must be removed. To achieve this aim, the three-sigma edit rule technique was applied [17]. This method is based on the difference between each value and the median of the signal:

$$MADN(p) = \frac{Median\{|S(p) - Median\{S\}|\}}{0.6745}$$

where S is the full spindle load signal and p is the number of machined pieces. The robust three-sigma edit rule establishes that the observation $S(p)$ is an outlier if: $|S(p) - Median\{S\}| > r$, where r is a threshold value. In this case, $r = 3$ is set with expert supervision.

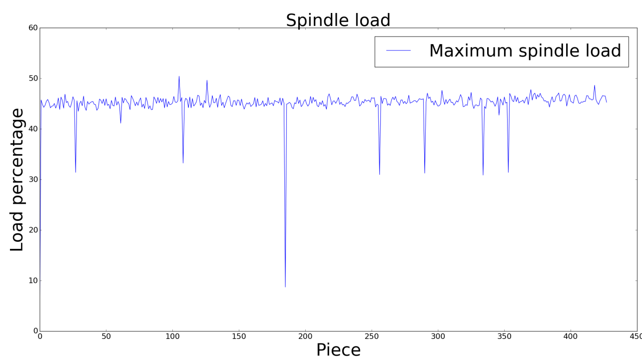

Figure 3: One time series spindle load before outlier removal.

As a second step, and once the outliers were removed, we transformed the series by a smoothing method. The Savitzky–Golay [43] and Wiener [44] smoothing methods were tested. Savitzky–Golay is a smoothing method based on moving average value. In particular, in this work, $S(p)$ being the value of the series in the p^{th} machined piece or point, Savitzky–Golay determined a new $S_f(p)$ by calculating a cubic polynomial with $n = 7$ values around the point p:

$$S_f(p) = C_{p-(n-1)/2} * S(p-(n-1)/2) + \ldots + C_p * S(p) + \ldots + C_{p+(n-1)/2} * S(p+(n-1)/2) \ ,$$

where C_p is the coefficient associated with the p^{th} point on the polynomial approximation.

The Savitzky–Golay filter was the transformation that obtained a better visualization of the signal and enabled detecting the main trends on the series, which was the main issue of this part of the study.

Taking into account that some of the signals had different behaviors (see Figure 4), a final step in data processing was carried out. This reduction was obtained by applying an iterative clustering method. This methodology provided a two group classification based on K-means on each iteration, and if one of the groups had less than 10% of the signals, those signals were not considered as normal or regular behavior. The One Class-Support Vector Machine (OC-SVM) [45] classification method was applied as a validation of the clustering method mentioned above. This method generated a hyperplane where the normal behavior was found and separated those abnormal values. Validation was obtained successfully. Finally, with the selected regular series, machine learning techniques were applied to estimate the RUL.

5.4. Concept Drift Detection

Having such an amount of data acquired over a long time made it necessary to identify whether there was a concept drift or not in order to select the appropriate signals for RUL estimation. The concept drift search was done to identify whether the machine suffered some wear during this time. We sought two different types of concept drift. On the one hand, concept drift detection for the hole machine was suggested. This approximation was done taking all the maximum spindle values for every machined piece and a linear regressor, and no tendency over time was detected, which enabled us to use all the signals for the RUL detection. This could be due to the big machine lifetime compared to the period we observed. On the other hand, a concept drift for each tool was sought. This detection was done by studying the evolution of the errors derived from regression models built for each series. Some values of the series were selected at random, and the predicted

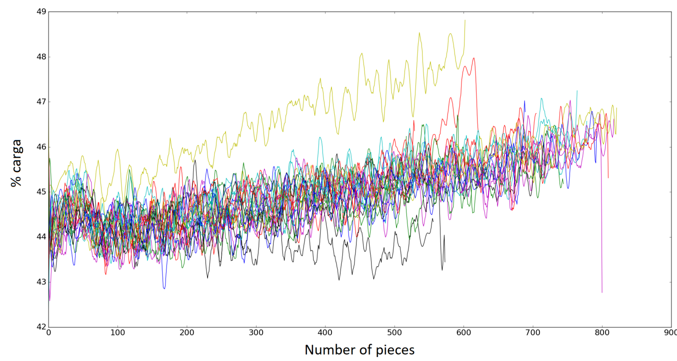

Figure 4: Time series after smoothing transformation in a period of time.

and observed values were compared to the obtained error. If this error (Mean Squared Error MSE (Equation (1))) grew for each forecasting piece, it would indicate that there was a concept drift. In the case we studied, no concept drift was detected for the tool.

$$MSE(S_f) = \frac{1}{n_S}\sum_{p}(S_f(p) - \hat{S}_f(p))^2 \qquad (1)$$

where S_f is the observed series and $\hat{S}_f$ is the predicted series.

5.5. Decision Making Application for RUL Estimation

Customers always want to obtain some digital device that enables seeing the online state of the process. Therefore, we worked on models to be implemented in real time on the machine. Approximation was made with linear and quadratic regressions. In similar mechanical processes, Cortadi et al. [46] showed that quadratic approximation was the one that fit best. Nevertheless, in this particular machining process, the second order curve introduced some physical incoherence in some of the series, and the first order approximation gave better results. This approximation has been developed, and currently, it is accessible at the machine itself (see Figure 5). Based on the data acquisition platform (see Figure 5), it provided a visualization of the acquired signals along the machining process. This visualization could be made not only for historical data (from the database associated with the tool), but also for actual series. Moreover, as can be seen in Figure 5, an estimation of the RUL in terms of the amount of remaining pieces the tool could still machine safely is given, and this value was obtained by applying a linear regression to the pieces machined until that point and determining when the line would go past a threshold. Also shown are the number of pieces machined during a whole day (Figure 5, top) and a particular series with a linear regression (Figure 5, bottom), which provided the aforementioned estimation before the replacement of the tool was required. This application offered a means to have a predictive maintenance instead of the preventive maintenance used before.

Figure 5: Application integrated at the machine showing the Remaining Useful Life (RUL) for the actual working tool.

5.6. Remaining Useful Life Assessment

For an offline prediction of the spindle load, other models were applied. These models were: ARIMA [47], Gradient Boosting (GB) [48], Random Forest (RF) [49], and Recurrent Neural Network (RNN) [50].

With all the regular series identified in the data processing step, a mean series was built. To evaluate the predictive ability of the models, the training set was made of the first part of the series and the test with the last p values: 10, 20, 30, 40, and 50 values of the series. The ARIMA model was generated with the series itself, while GB, RF, and RNN were developed with the input of the value of the series on each instant t and the previous 9 $t-1, t-2, \ldots, t-9$, so that 10 values were taken into account for prediction. In all the models, the output of the model was the spindle load of the instances from $t+1, t+2, \ldots, t+p$. The obtained results are shown in Table 1 and present the MSE of the p predicted values against the measured ones. Notice that the values were multiplied by 10^{-3}.

Table 1: Mean MSE values for each method for each different number of test pieces (multiplied by 10^{-3}). GB, Gradient Boosting.

Test Pieces	**ARIMA**	**GB**	**RF**	**RNN**
10	3.668	3.832	4.050	4.256
20	2.832	3.227	2.891	3.524
30	3.166	3.833	3.325	3.885
40	3.909	3.489	3.121	3.756
50	3.791	3.899	4.065	4.002

The results were shown to be good, and in Figure 6, the prediction obtained by each model and the real signal (blue) can be seen. This figure was made with 20 test pieces, while all tested values had similar results. It was shown to have good accuracy in the short term, but the strength was lost in the long term, which implied that an extension of the machining process could be done, while an RUL value could only be suggested once the process was near the threshold.

On the other hand, the ARIMA, GB, RF, and RNN models we obtained for the mean regular series were applied on each series separately. Some random series were taken for the validation of the models in order to define if the machining process could be extended in time. As long the machine had a preventive maintenance, these methods were demonstrated to enable the tool

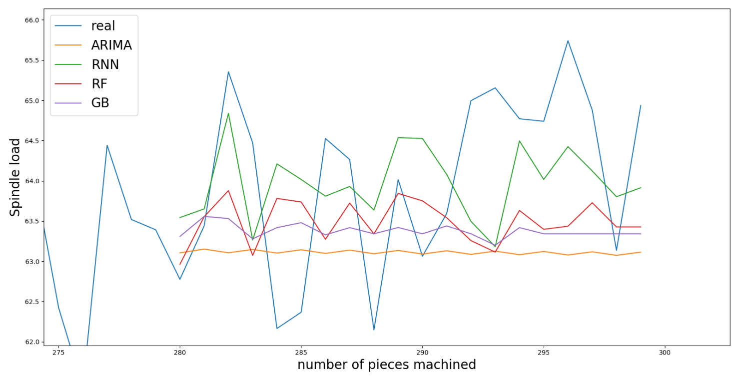

Figure 6: Prediction for the mean series of each regressor.

to increase the number of pieces machined at least by 20 pieces more; this value is determined in Table 1 as the more accurate one. The spindle load of 115 series was studied, and it could be concluded that for 113 of them, the tool's lifetime could be extended. For only two of the series, the threshold was passed, and an earlier maintenance was suggested.

In Figure 7, a flowchart representing the main steps applied on this methodology is provided. First, the spindle load acquisition data are presented. These data needed to be discretized before a characterization was applied. This discretization is shown in Figure 7b. The characterization was based on expert knowledge, and each piece's maximum value was extracted. For each tool, a new time series was developed (see Figure 7c). The obtained series were cleaned and smoothed for better prediction, and future value prediction was developed. Figure 7d shows the ARIMA approach of one series, and Figure 7e presents the comparison between all the machine learning methods applied in this work.

Since this work provided a customized solution for a real problem in a factory, as far as we know, there are no works from which comparative results to the solution we found could be obtained. Nevertheless, some similarities were found with [42]. These similarities were:

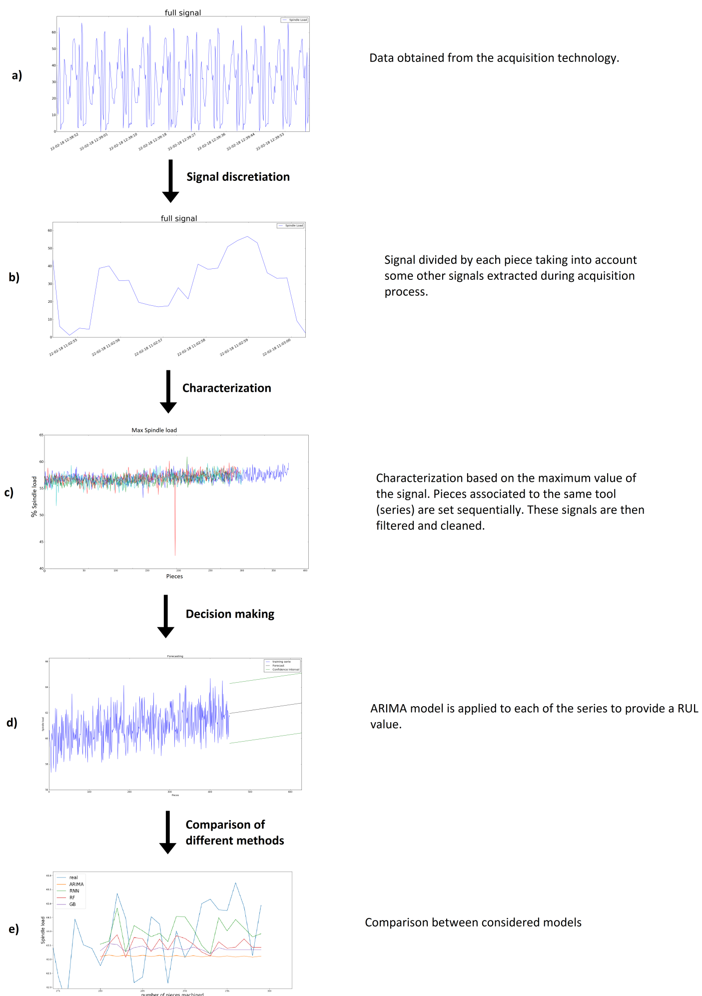

Figure 7: Flowchart of the main steps of the methodology exposed in this work.

- RUL estimation.
- Application in a discrete machining process.
- Characterization of the signal acquired (Health Indicator (HI)).

Although the goal and the main steps were similar, there were some differences:

- Djeziri et al. [42] did not apply any preprocessing technique to the raw data.
- Djeziri et al. [42] developed an RUL estimation based on an extrapolation, while the present work applied some machine learning models and a comparison between them.

Even if these two works cannot be compared numerically, it can be said that the methodology applied in this work was coherent with the one developed by Djeziri et al. [42]. The mentioned differences provided a more complex methodology, which enabled more accurate and robust predictions.

6. Conclusions and Future Work

This study achieved two different goals: First was an application developed to visualize the RUL in a machining process that was based on a linear regression model, which was actually based on the production, providing a predictive maintenance. The application was updated each time a new machining series began. Second was to obtain more accurate results to predict the RUL for comparison. Although accuracy was gained, the complexity of the models made their implementation more difficult in the production machine.

In this work, a methodology that could be applied not only in this process, but also in most of the processes for serial production of pieces was provided. Similar processes will be studied with this approach to validate this methodology with some limitations. The signal considered to predict the RUL was the spindle load, but it is our aim to include other signals and study their contribution to obtain a better explanation of the process and more accurate RUL prediction. Furthermore, as the spindle of the process was made of two different tools, two different RUL predictions needed to be done, each one for each tool. Finally, we are working to increase the frequency acquisition of the signals. This increase would improve the characterization of the signal and hence enable recording more features, which could explain the process better and develop more accurate models.

authorcontributions conceptualization, A.J. and G.R.; methodology, A.J. and F.B.; software, A.J and I.I.; validation, A.J., I.I. and B.S.; formal analysis, F.B.; investigation, A.J.; resources, G.R.; data curation, A.J.; writing–original draft preparation, A.J.; writing–review and editing, A.J., F.B. and I.I.; visualization, A.J.; supervision, B.S.; project administration, G.R.; funding acquisition, G.R.

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5.2.2. Time series forecasting in turning processes using ARIMA model

- **Titulo**: Time series forecasting in turning processes using ARIMA model.
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A prediction model which is able to predict the tool life andthe cutting edge replacement is tackled. The study is based on thespindleload during a turning process in order to optimize productivityand thecost of the turning processes. The methodology proposed to address theproblem encompasses several steps. The main ones include filtering thesignal, modeling of the normal behavior and forecasting. The forecastingapproach is carried out by an Autoregressive Integrated Moving Average(ARIMA) model. Results are compared with a robustARIMAmodeland show that the previous preprocessing steps are necessary to obtaingreater accuracy in predicting future values of this specific process.

Time Series Forecasting in Turning Processes Using ARIMA Model

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Abstract. A prediction model which is able to predict the tool life and the cutting edge replacement is tackled. The study is based on the spindle load during a turning process in order to optimize productivity and the cost of the turning processes. The methodology proposed to address the problem encompasses several steps. The main ones include filtering the signal, modeling of the normal behavior and forecasting. The forecasting approach is carried out by an Autoregressive Integrated Moving Average (*ARIMA*) model. Results are compared with a robust *ARIMA* model and show that the previous preprocessing steps are necessary to obtain greater accuracy in predicting future values of this specific process.

Keywords: Robust statistics · Process normality detection
Time series forecasting · ARIMA models

1 Introduction

The maintenance of machining processes is one of the most studied topics in manufacturing industry, due to its relevance for the process behavior and the economic impact on the production plans. Two different maintenance methods are applied in most of the industries; On the one hand, preventive maintenance, based on the theoretical life of the tool, which is commonly instigated by a periodic alarm. On the other hand, predictive maintenance uses strategies such as inferring the remaining useful life (*RUL*) of the tool, which mostly depends on the wear measurements. It is critically important to assess the RUL of an asset while in use since it has impacts on the planning of maintenance activities, spare parts provision, operational performance, and the profitability of the owner of an asset [17].

The objective of predictive maintenance is to predict when equipment failure may occur and to prevent a failure by performing maintenance. Ideally, this approach enables the system to have the lowest possible maintenance frequency. Many techniques can be used in order to achieve this aim, which heavily depends on the process studied. These techniques must achieve two main goals: being effective at predicting failures and providing enough time for upcoming maintenance.

This study is applied to a machining process in the automotive sector. The workpiece is a bearing conic ring. The material machined was Steel 100Cr6. The machining operation was cylindrical turning with two toolposts, one to mechanize the internal surface of the part and another one for the external surface.

The experiments were conducted on a CNC turning centre with two toolposts which can be moved into two axes independently with longitudinal and cross feed movement. The cutting tool holder used was a C3-MTJNR-22040-16 equipped with a TNMG160408-PF insert for the external surface and a special tool holder equipped with a WNMG060408-PM insert for the inner diameter. During the machining process the rotating revolutions were set to 1800 rpm.

This work has the aim of improving tool life in a particular turning process. This will enable the machine to have a lower number of tool changes which means that more pieces can be machined each year. This goal can be obtained by the prediction of the spindle load charge. Robust ARIMA methods are able to preprocess the signal before obtaining the prediction. In this study, a new preprocessing method is developed with expert process knowledge and ARIMA model is used for prediction. The developed method is compared with robust model and results shows that the preprocessing is necessary since an increase of the accuracy of the robust method forecasting is obtained.

The paper is organized as follows. Section 2 shows an analysis of the state of the art about remaining useful life RUL and different approaches generally used. Section 3 presents the methodology applied, whose results are in Sect. 4. Finally, conclusions and future work are exposed in Sect. 5.

2 Related Work

Extracting theoretical and empirical knowledge of an industrial process is one of the most important issues in manufacturing. The machining industry is interested in modeling their machines in order to have more efficient maintenance planning for unexpected behaviors. Data based modeling is a step forward when improving maintenance strategies applied to the machine in terms of predicting remaining useful life RUL, and knowing if the tooling process will maintain its function over time [10]. A wide variety of models have been developed for time series prediction, such as support vector machines(SVM) and their regression version Support Vector Regressors (SVR) [12], finite element models and also Autoregressive integrated moving average ($ARIMA$).

Among these, the $ARIMA$ model has turned out to be one of the most popular time series forecasting models. Yuan et al. [19] applied this method in order to predict China's primary energy consumption and compares it with a Gray differential model (GM). ARIMA models are also used in applications such as prediction of electricity prices [8] and gas demand [3]. The $ARIMA$ forms a general class of linear models that have historically seen wide use in modeling and forecasting time series [4]. ARIMA models are derived from the more common Autoregressive Moving Average (ARMA) model, which models a time series using two parts, an autoregressive (AR) part and a Moving Average (MA) part. However, since ARMA models can only be used to model stationary processes ARIMA models are often employed, as they can be used to model non-stationary time series signals. Applications and studies in RUL with ARIMA models can be seen in some works in the literature. For example in [13,16] evaluate the performance of different methods, including ARIMA, to predict the RUL of Lithium-ion Batteries is evaluated. Wu et al. [18] proposes an improved ARIMA approach to predict the future machine status, the prediction of the vibration characteristic in rotating machinery.

In this work, we analyze the ARIMA approach by comparing a preprocessing methodology with a robust ARIMA method.

3 Methodology

In this section the methodology used for experiments is explained. First of all we need to monitorize the process, where the acquired data is obtained with specific hardware for machining processes, which provides several measurements obtained during the turning process. These signals are obtained with a frequency of 5 Hz, which may be increased in future developments. In this work spindle load is studied as this is the main variable regarding the wear and the tool life of the process according to expert knowledge.

The used signal is obtained as a collection of observations made sequentially through time, a time series (see Fig. 1). These time series are divided into smaller ones that are associated to a tool and when the tool is changed the series ends, which are denominated manufacturing sequence. Each tool machines multiple pieces until the tool is changed due to a preventive maintenance rule. Once a sequence is finished, that tool is removed and another tool is taken for the next manufacturing sequence. The signal corresponding to a piece is cropped by experience with another signal acquired in the process, so we are able to indicate the beginning and the end of each piece as can be seen in Fig. 2.

In this work, each sequence is studied separately applying the methodology explained in the following paragraphs: characterization, outliers detection, filtering, abnormal behavior detection and forecasting.

3.1 Characterization of the Signal

This is a matter of representing or characterizing a signal fragment defined as a time series T, by means of a vector of values F. This vector can have a temporal relation or not, depending on the technique that is used.

$$T = (t_1, ...t_n) \Rightarrow F = (f_1...f_P) \qquad where\ n >> P\,,$$

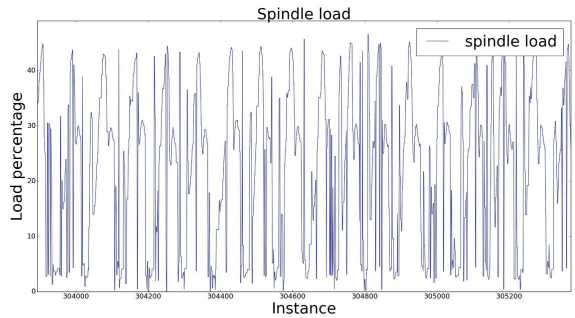

Fig. 1. Spindle load time series associated to a tool including 16 pieces.

That way, the initial length of the series T, n, is notably reduced to length P. Several time-series representations have been proposed as exposed in [2]. As a starting point of this work, we are going to use a simple but effective feature according to expert knowledge and it is explained int he following lines:

As the pieces are machined with a similar effort from the tool as can be appreciated in Fig. 2, in the case studied here the maximum value applied by the spindle is selected as the most important value; these maximum values are ordered according to the manufacturing sequence providing a new time series. These time series are the ones we will analyze in the rest of this work to infer the RUL of the tool.

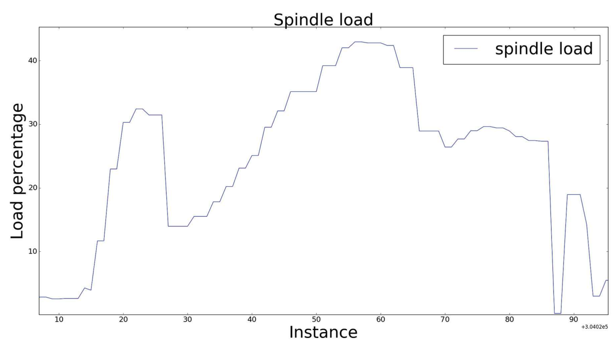

Fig. 2. Spindle load charge on a piece, extracted from the time series.

3.2 Outlier Detection

Let F be the time series signal obtained from the characterization and p the number of piece corresponding the value $F(p)$. Low acquisition frequency implies to have some not well measured values. This produces some outliers in the time series, which do not represent the monitorizing process well. Those values, known as outliers, must be deleted from the signals. To achieve this aim [14] proposed *three sigma edit rule* method which has been applied by [9] in his work on instability detection.

This simple robust method allows a median value to be obtained of each force component $Me = Median\{F\}$ and the corresponding absolute standard deviations, which are given as:

$$|F(p) - Me_F|, \quad p = 1, \ldots, P;$$

where P is the number of machined pieces for a series.

The median value of these deviations is calculated and divided by 0.6745 as indicated in [14]:

$$MADN(p) = \frac{Median\{|F(p) - Me_F|\}}{0.6745}$$

The robust three-sigma edit rule (see Maronna [14]) establishes that the observation $F(p)$ is an outlier if:

$$|F(p) - Me_F| > r$$

where r is a threshold value. Under the normality assumption, often $r = 3$ is set (hence the "three-sigma rule") and it is the value set in this work. Observations beyond the threshold are considered as outliers. In order to compare different series, detected outliers (machined pieces) are removed from all the original series.

3.3 Filtering

In order to visualize any trend in the time series, a filter to smooth the trend is applied. There are lot of filters in the bibliography that enables us to achieve this goal. In this study, a comparison between 2 of them is made as was suggested in [11].

On the one hand, Savitzky-Golay [6] is applied, which uses a polynomial approximation of the nearest data, where polynomial degree g and the number of points q are parameters that must be set up by experience. Let F be the time series which is filtered. On each point p, a new value is determined by the function:

$$F(p) = a_0 + a_1(p - p_0) + a_2(p - p_0)(p - p_1) + \ldots + a_g(p - p_0)(p - p_1) \ldots (p - p_{g-1})$$

where $a_0, \ldots, a_g$ values are determined by the g nearest points $(g-1)/2$ previous ones, $(g-1)/2$ ones after and the pth value. Note that g is an odd number and $q > g$.

On the other hand, Wiener filter [5] is studied, which is linear least square error filter, based on statistical estimations of the signal. The Wiener filter works in the frequency domain and requires knowledge of the variances of the signals.

3.4 Abnormal Behavior Detection

To achieve this objective, first, those series which are considered as abnormal must be detected and removed. Due to the fact that the current maintenance of the process is based on preventive maintenance with a simple rule, there are series that must be removed as they do not fulfill the criteria laid by the rule.

Second, series which are extremely different from the rest are deleted in order to keep the normal ones. This is obtained through the application of an iterative K-Means, where if a cluster C_1 is small compared to C_2, that is 10 times smaller or more, all the signals in C_1 are removed and the process is repeated until the clusters have a similar shape. This concludes with an amount of series that are similar. Based on those series, a mean series, which represents the normal behavior of the process is calculated.

3.5 Forecasting

Forecasting is always a goal in a huge variety of fields. In machining processes, predicting breakdowns enables the process to be more efficient. To this aim, a wide variety of techniques have been used. One of the most important and widely used time series forecasting models is the autoregressive integrated moving average *ARIMA* model [7], which is used in this study.

In the case of a time series model, the effect of outliers is more serious than in a regression model because the presence of an outlier at time t affects not only that period but also subsequent periods. Robust ARIMA estimates based on a recursive robust filter replaces the observations suspected of being outliers with cleaned values.

For the forecasting of the spindle two approaches are compared; First, an ARIMA model for forecasting is developed in [15], which is combined with preprocessing approach explained in previous sections: outlier detection (Sect. 3.2), filtering (Sect. 3.3) and abnormal detection (Sect. 3.4). Second, a robust ARIMA method is used [1]. This robust method is applied to raw data without any preprocessing.

4 Results

As previously explained, for each machined piece a representative value is extracted, which in this case is the maximum load during the process. Figure 2 shows which value is extracted from the signal. This feature extraction is made for all the machined pieces of the series, and ordering those values sequentially a new time series is obtained (see Fig. 3). This series is shown to have some outliers, which are caused by the data acquisition frequency, and must be removed

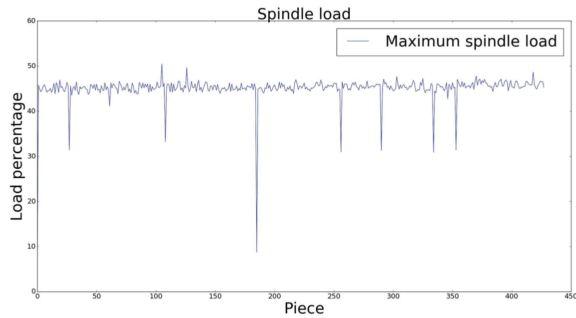

Fig. 3. One time series spindle load before outlier removal.

in order to obtain an appropriate signal. This removal is obtained with the three-sigma edit rule method.

To reduce signal noise and to detect sequence trends, a filter is applied to the signal. In this study, two different filters are applied, which are shown in Fig. 4. It is appreciated that *Savitzky-Golay* filter achieves the aim of detecting sequence trends better, thus this is the method selected for the results analysis. The series are now as shown in Fig. 5.

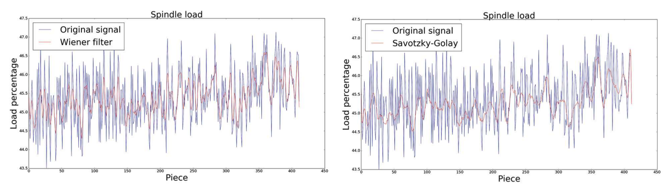

Fig. 4. Both *Wiener*(left) and *Savitzky-Golay*(right) filters applied to one signal.

At this point, in order to obtain a sequence which explains the process normality, some of the series must be removed. First, series which are less than 500 pieces are removed, which is the number of pieces for preventive maintenance in the machine nowadays (see Fig. 5). Next, a K-Means clustering is applied with two clusters in order to remove abnormal series such as the purple one shown in Fig. 5.

With all the 22 remaining series, a mean value is calculated, which is considered as a normality model and which is used for predicting spindle load values. This signal is used only for the *ARIMA* model, while robust *ARIMA* is used with raw data.

Signal is divided into training and tested values, where 96% of the data are extracted for the training one. In Table 1, obtained results are exposed, where it can be seen that the prediction with *ARIMA* model with the preprocessing

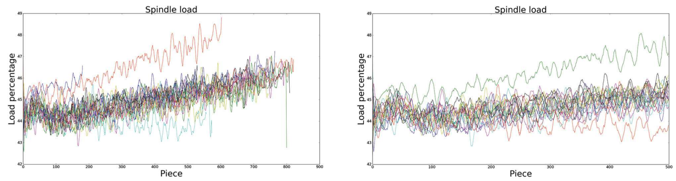

Fig. 5. All the series filtered (left). The series with more than 500 pieces machined (right) (Color figure online).

alternative is better. This suggests that the preprocessing performed on this process is necessary.

Table 1. Differences between real data and predicted value.

	t_1	t_2	t_3	t_4	t_5	t_6	t_7	t_8	t_9	t_{10}
Robust method	12.68	15.23	14.28	14.18	15.40	16.14	15.51	13.61	14.79	14.85
ARIMA model	2,20	4,66	3,62	3,83	4,96	5,76	4,99	3,10	4,33	4,38

Finally, based on the whole signal, future predicted values are calculated. Results (see Table 2) show that the spindle load is still controlled and therefore more pieces could be machined.

Table 2. Forecasting spindle values values.

	t_1	t_2	t_3	t_4	t_5	t_6	t_7	t_8	t_9	t_{10}
ARIMA model	45.24	45.27	45.32	45.21	45.40	45.25	45.35	45.33	45.32	45.35

5 Conclusions and Future Work

In this paper a methodology to predict spindle load values is carried out. Within this approach a new preprocessing method based on the expert knowledge of the process and *ARIMA* forecasting are developed. The results are compared with a robust *ARIMA* method which a priori could work in the presence of outliers and without previous preprocessing. Nevertheless it is shown that the preprocessing included in the approach increases the accuracy obtained, appearing the preprocessing as necessary. Forecasting values for ARIMA model has shown that machine could extend its *RUL*.

In order to obtain a better abnormal behavior detection to model the process, new strategies will be developed with more variables captured by the hardware. Obtaining a different characterization of each piece and increasing the acquired frequency for the spindle load signal is also proposed for future work.

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5.3. Hibridación de datos y predicción de *RUL* en rodamientos.

- **Title**: A hybrid approach for synthetic data generation and advanced prognostics.
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Maintenance decision support can be highly boosted by Artificial Intelligence, which is able to accurately model behaviours of interest from monitoring data and anticipate critical events. In recent years, hybrid methods have increased in popularity due to their ability to mix different data-driven learning models that combine real and synthetic data, these latter representing behaviours of interest that are very difficult to obtain or even not available. They can be used in complex industrial scenarios to successfully learn flexible and accurate mathematical models in order to establish the current and future system health status, predicting sub-optimal working conditions and critical events in an online fashion. In this paper, a novel hybrid approach for synthetic data generation, behavioural pattern extraction and advanced prognostics of industrial assets is proposed. In accordance to the physical properties of a particular industrial asset, its health condition is assessed by analysing the vibrational data on the basis of the online fitting of an ensemble of machine learning methods. Finally, the Remaining Useful Life (RUL) of the asset is estimated, allowing to optimally schedule the required maintenance operations before the asset fails drastically, and thus minimizing the costs and risks related to unscheduled stops. The proposed approach is validated on a real ball bearing system.

A hybrid approach for synthetic data generation and advanced prognostics

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ABSTRACT Maintenance decision support can be highly boosted by Artificial Intelligence, which is able to accurately model behaviours of interest from monitoring data and anticipate critical events. In recent years, hybrid methods have increased in popularity due to their ability to mix different data-driven learning models that combine real and synthetic data, these latter representing behaviours of interest that are very difficult to obtain or even not available. They can be used in complex industrial scenarios to successfully learn flexible and accurate mathematical models in order to establish the current and future system health status, predicting sub-optimal working conditions and critical events in an online fashion. In this paper, a novel hybrid approach for synthetic data generation, behavioural pattern extraction and advanced prognostics of industrial assets is proposed. In accordance to the physical properties of a particular industrial asset, its health condition is assessed by analysing the vibrational data on the basis of the online fitting of an ensemble of machine learning methods. Finally, the Remaining Useful Life (*RUL*) of the asset is estimated, allowing to optimally schedule the required maintenance operations before the asset fails drastically, and thus minimizing the costs and risks related to unscheduled stops. The proposed approach is validated on a real ball bearing system.

INDEX TERMS
Ensemble methods, Hybrid approach, Machine learning, Predictive maintenance, Remaining useful life, Synthetic data generation.

I. INTRODUCTION

With the rapid development of Industry 4.0 technologies, paradigms such as big data and Industrial Internet of Things (*IIoT*), are increasing its applicability on industrial processes, where traditional technologies are evolving and being replaced. On many manufacturing and production processes, however, digitalization is still in an early stage, mainly due to the reluctance of the sector main actors when adopting and integrating all the digital concepts provided by this so-called fourth industrial revolution [1].

Under this scenario, the importance of maintenance has increased very rapidly in recent years due to the change in strategies that Industry 4.0 has caused, including the accurate prediction of the *RUL* of an asset. It provides important costs reduction associated to unexpected system brakedowns, service cuts and the minimization of risks and maintenance operations to be performed in order to assure an optimal working operation and production quality. To this aim, digital twins are being developed, which are based on the physical behaviour of the process. They can be improved in terms of accuracy by performing a fine-tuning with the help of real operational data directly acquired from the asset under study, and thus obtaining more realistic skills.

Unfortunately, in real industrial processes data acquired are not diverse enough to represent all the possible asset behaviours or some critical working conditions are not available for security reasons. This important gap is usually addressed by using domain expert knowledge, which can be obtained through physical models that describe the asset from an operational perspective. To go through this issue hybrid models are developed, where a physical model can be completed with the data acquired during real operation of the industrial assets. A hybrid model-based approach can lead with dynamic system modelling by combining data-driven models with physics models in time-varying service equipment [2].

In terms of *RUL* prediction, a huge amount of different machine learning models to be learned are available nowadays. It can be said that there is not an specific model that always obtains the best accuracy, given the fact that there is always a high dependency on the industrial process and the opreational context of the asset. To address these issue, in many reseach works the fusion of various models, denoted as hybrid or ensemble methods, is proposed. These models provide the capacity of integrating the data-driven modelling skills of different algorithms and finally produce a combined prediction with better accuracy.

In this work a novel approach for advanced prognostics is proposed on the basis of the synthetic data generation to represent not available events and patterns of interest, e.g.: critical and not optimal working conditions of the assets. The resulting diverse and enriched dataset, is used to fit a hybrid data-driven machine learning model, which is an ensemble of various methods that are fused to establish an optimal *RUL* prediction methodology in an stacking structure. All this work is validated on a real ball bearing system.

The rest of the article is organized as follows. Section II presents a review of related and previous works regarding hybrid models for improving assets reliability, and considering three different configurations; i.e.: hybrid ensemble learning models, sequential hybridization and physical hybridization. Section III explains the proposed methodology for advanced prognostics using real and synthetic data. Section IV explains a real and challenge industrial case study related to a ball bearing asset and the experimental results obtained are presented and discussed. Finally, the conclusions achieved in this study and the future research lines are given in the last section.

II. RELATED WORK

Industrial systems and subsystems modelling is becoming more important in the industrial sector. It is a key advantage for those who want to improve their production and properly manage the maintenance of the assets involved in the industrial processes. To achieve this aim, there are three different types of modelling; i.e.: physical, data-driven and hybrid models. The first two modelling types has been applied to a wide variety of industrial sectors, such as oil, manufacturing, solar energy or traffic flow. Hybrid models have not been studied so deeply but yet they have proven to obtain better forecasting accuracy than single-type models [3]. Even if most of the related research work is focused on model hybridization, there are other hybridization configurations that are gaining a lot of attention from the academic field, which are sequential hybridization and physical hybridization. In this section some of the most recent and relevant research works in the hybrid-modelling topic are commented.

A. HYBRID ENSEMBLE LEARNING MODELS

Model hybridization methodology is based on the fusion of multiple data-driven models in order to produce more accurate predictions, which is also known as *ensemble fusion method*.

[4] proposed a new model that combines a least squares Support Vector Machine (*SVM*) method, together with particle swarm optimization (*LSSVM–PSO*) and the Generalized Autoregressive conditional heteroscedasticity (*GARCH*) model, to forecast crude oil prices. [5] considered the periodicity and variability of traffic flow and limitations of single prediction models to develop an adaptive hybrid model for predicting short-term traffic flow. Firstly, the linear Autoregressive Integrated Moving Average (*ARIMA*) method and non-linear Wavelet Neural Network (*WNN*) method were used to predict traffic flow. Then, outputs of the two individual models were combined by fuzzy logic and the weighted result was regarded as the final predicted traffic volume of the hybrid model. [6] applied a hybrid method based on unsteady Reynolds Averaged Navier–Stokes simulations and a *Ffowcs Williams and Hawking's analogy* to investigate the noise generated by a radial blower in a free-field environment. An evaluation of the influence of various conditions have been studied. [7] studied the porosity and permeability with a hybrid modelling which was based on the combination of three existing Artificial Intelligence techniques: Functional Networks, *SVM* and Fuzzy Logic System, by applying the functional approximation capabilities of Functional Networks, the ability of Fuzzy Logic to handle uncertainties and the scalability and robustness of *SVM* in handling small and high-dimensional data to six datasets. The work demonstrate successful results of the hybridization in one of the real-life problems encountered in oil and gas production. In [8], a Kernel density-based outlier detection method is combined with a ν-*SVM* model to estimate the health status of marine propulsion systems from monitoring sensor data, studying the fault propagation on different subsystems over time. The work presented in [9] proposes an architecture to implement a hybrid approach. It consists of a two level strategy; first, anomalies and trends are detected locally; second, virtual commissioning uses cloud computing technologies for further analysis. [10] proposes a comparison between three models: seasonal autoregressive integrated moving average (*SARIMA*) models, SVM model and a hybrid model made with both of them. In order to determine the best method, the Normalized Mean Square Error (*NMSE*) and the Mean Absolute Percentage Error (*MAPE*) are calculated and hybrid model shows better accuracy. [11]

exposed 3 data-driven models: Support Vector Regression (*SVR*), a Long Short-Term Memory (*LSTM*) network and a modified data-driven model, i.e., the improved pattern sequence similarity search (*IPSS*). A hybrid model based on these three models was then proposed to predict natural gas spot price in the U.S.

B. SEQUENTIAL HYBRIDIZATION

Sequential hybridization is based on the application of different algorithms in each stage of the learning process to obtain better data or parameters for the following model.

[12], for instance, propose a machine tool selection method based on a novel hybrid multi-criteria decision making (*MCDM*) model. Firstly, a comprehensive weight technique is employed applying fuzzy decision-making trial and evaluation laboratory (*FDEMATEL*). Secondly, later defuzzification VIKOR (*LDVIKOR*) is put forward to rank the optional alternatives. Finally, a case application testes the proposed method. [13] developed an accurate prediction of maximum depth of pitting corrosion in oil and gas pipelines with an efficient hybrid intelligent model based on *SVR*. The selection of the parameters applied to *SVR* is obtained by the performance of well-known meta-heuristic optimization techniques, such as Genetic Algorithm (*GA*), Particle Swarm Optimization (*PSO*) and Firefly Algorithm (*FFA*). Hybrid models are developed to integrate *SVR* with *GA*, *PSO*, and *FFA* techniques. A comparison with the traditional *SVR* model shows better accuracy in the results. This hybrid method is supposed to be adopted to support pipeline operators in the maintenance decision-making process of oil and gas facilities. [14] developed a neural network ensemble approach which significantly improved generalization performance. One novel selective neural network ensemble model is suggested for bearing degradation process prediction. Optimal parameters are selected by an improved particle swarm optimization with simulated annealing subset formed by accurate and diverse networks. This enables the system to obtain a better ability to escape from the local optimum. [15] propose a hybrid intelligent method for multi-fault detection of rotating machinery. Three algorithms are combined including the redundant second generation wavelet package transform (*RSGWPT*), the kernel principal component analysis (*KPCA*) and the twin support vector machine (*TWSVM*). *RSGWPT* is used to extract feature vectors from representative statistical characteristics, *KPCA* is performed to reduce the dimension of features and to extract the dominant features for the following classification. Finally, a twin support vector machine is used to construct a multi-class classifier. Inputting superior features to this classifier, the condition of the monitored machine component can be determined. [16] propose a new deep learning based fault diagnosis method, which extracts features from both time and frequency domains.Experimentation on gearbox, rotor and engine rolling bearing are applied. Local and global principal component analysis (*PCA*) is developed to reduce feature dimensionality and an ensemble kernel extreme learning machine is proposed for fault pattern classification. The authors in [17] developed an approach that first modeled the behaviour of different systems in marine diesel engines using symbolic regression, and then they applied a deep neural network based on LSTM units over the predicted time series data aiming at doing prognosis.

C. PHYSICAL HYBRIDIZATION

Physical hybridization refers to the hybrid models developed by the fusion of a physical model and data-driven models.

[18] developed a hybrid predictive maintenance method for *CNC* machine tools driven by Digital Twin model and Digital Twin data. Both models are fused by particle filtering method and applied for RUL prediction. [19] evaluates the accuracy of two physical models and two models based on artificial neural networks (*ANN*) that use meteorological data as input variables. Then, a hybrid technique is proposed, using the time series generated by the individual models as inputs of a new *ANN*. [20] propose a hybrid point-particle force model to predict fluid mediated interactions between solid particles.

In this research work a novel prognostics approach based on real and synthetic data is proposed. First, a set of diverse synthetic data representing behavioural patterns of interest, namely not optimal and critical working conditions, are generated by means of analytical models. Then, the resulting augmented dataset is used to fit a hybrid model of predictive machine learning methods that is able to finally produce an accurate asset *RUL* estimation.

In the next section the proposed hybrid prognostics approach for addressing predictive maintenance tasks in complex industrial scenarios is described in detail.

III. PROPOSED HYBRID APPROACH

In the present research work, a hybrid approach based on a two-stage data generation and learning process is envisaged. They are the following:

- Synthetic data generation for behavioural pattern extraction. Behaviours and patterns of interest are sampled using real data and analytical models given in the literature and supported by domain expert knowledge. The resulting dataset is thus diverse enough and it will contain normal behaviours and anomalies, which are finally applied to fit the hybrid ensemble prediction system with enriched information.
- Ensemble methods for advanced prognostics. The prediction system is based on an ensemble machine learning methods that are combined in a stacking-based approach that provides a more accurate prediction.

These two hybrid methods, from both data generation and data modelling perspectives, are further described in the next subsections.

A. SYNTHETIC DATA GENERATION FOR BEHAVIOURAL PATTERN EXTRACTION

One of the key issues regarding industrial prognosis is on the acquisition of real data related to behaviours or events of interest, e.g.: not optimal and critical working conditions. For safety and production reasons, these behaviours are avoided by applying conservative and preventive maintenance strategies. This is due to the high impact that they have in the production system and the supply of services. Therefore, in order to assure the optimal operation of the assets, synthetic signals that represent behaviours of interest can highly support the data-driven analysis of their operational condition. Synthetic data generation requires a deep expert knowledge of the production system's assets and their physics, which is not always easily available. In several cases, however, some relevant information related to the assets' behaviour can be found in the literature.

In this study, data are acquired from an industrial asset and during real operation. This implies to only have data related to optimal working conditions. To address this lack of relevant information on data, a synthetic data generation process has been applied. This methodology enables to have a diverse and enriched dataset to train data-driven models more accurately and thus achieving the final goal of estimating assets' *RUL*. The main problem in the data generation phase is the need of integrating the domain expert knowledge, generated data must be coherent with the process to end up with a good quality model. Apart from domain knowledge, some literature has also been studied (see [21]–[23]) to determine the behavioural pattern for each working condition. These patterns are found in the frequency domain and that implies the need of transforming the original time domain data.

Data generation was mainly performed by modifying some peak values at particular frequencies in the range of each considered working condition on real samples. The pattern is analysed in frequency domain. Therefore, the raw vibrational signal, $\mathbf{x}$, which is acquired in time domain, are first transformed to the frequency domain. To do so, the Fourier Transform algorithm is applied to the signal $\mathbf{x}$. Fourier transform is a signal processing technique that decomposes a time domain signal into the series of frequencies (amplitudes and frequencies) that composed the time domain signal. It was first discussed by Joseph Fourier [24], and since then it has been further developed becoming a robust frequency domain method in modal analysis [25]. The basic idea of spectral analysis is to represent the original vibration signal as a new sequence, which determines the importance of each frequency component in the dynamics of the signal. Given that $\mathbf{x} = \{x_0, \ldots, x_{n-1}\}$ is the sampled signal, the Fast Fourier Transform (FFT) computes its representation in the frequency domain, as it can be seen in Equation 1.

$$A(f_k) = \sum_{j=0}^{n-1} x_j e^{-2\pi i\, k\, j/n} \tag{1}$$

where f_k represents frequency and $|A(f_k)|$ is signal amplitude in frequency domain.

Besides, the original signal can be rebuild with the inverse FFT, as it can be seen in Equation 2.

$$x_j = \frac{1}{n} \sum_{k=0}^{n-1} A(f_k) e^{2\pi i\, k\, j/n} \tag{2}$$

This signal analysis technique provides a powerful spectral based diagnostic method in stationary conditions, when there is no transient signals involved. In this frequency spectrum, some of the frequencies are more related with the operational conditions and therefore, the important ones to characterize the operational condition can be selected. Therefore, $\{0, \ldots, n-1\} = S_1 \cup S_0$ can be considered, being S_1 the subset with the important underlying frequencies. Those frequencies are the only ones which are modified as is presented in Equation 3.

$$x_j = \frac{1}{n} \sum_{k \in S_1} A(f_k) e^{2\pi i\, k\, j/n} + r_j \tag{3}$$

where $A(f_k)$ are the peak values associated to the relevant frequencies that are selected in S_1, and r_j is the remaining of the original signal. This allows generating new synthetic signals by just modifying the relevant amplitudes, as it is shown in Equation 4.

$$x'_j = \frac{1}{n} \sum_{k \in S_1} B(f_k) e^{2\pi i\, k\, j/n} + r_j \tag{4}$$

The new amplitudes $B(f_k)$ are generated so that 3 different patterns of interest are built; i.e.: optimal operational condition, non optimal operational condition and critical operational conditions, according to the behaviours described in [21]–[23].

An illustrative example of this method addressing the above mentioned 3 patterns is shown in Figure 1.

Therefore, the proposed method for synthetic data generation under industrial scenarios allows to successfully obtain a complete dataset that contains events related to patterns of interest that are not available, and hence giving the opportunity to obtain more accurate and robust predictive models.

Once the enriched and diverse dataset is formed, containing original and synthetic signals and gathering all operational conditions of interest, some key features of the signals concerning the time domain as well as the frequency domain are extracted. Normally, this feature engineering process is very time consuming and requires a deep knowledge on the application domain and on the signal shape of each pattern under study. But it is proven that it clearly helps to improve model accuracy on unseen data. Those features are the inputs used to build the prediction system as it is explained in the following section.

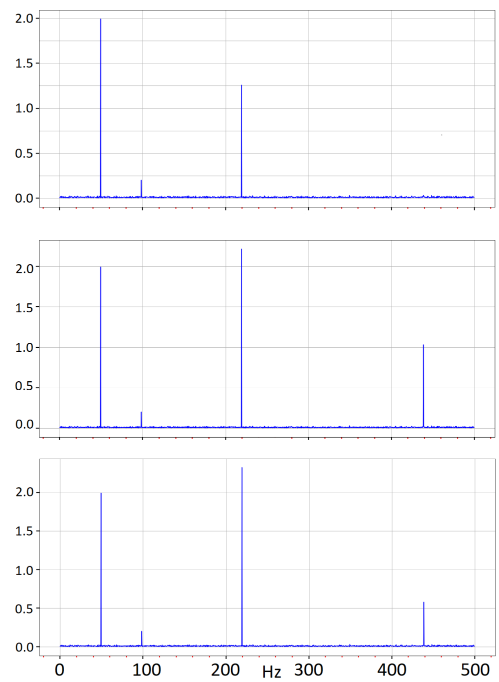

FIGURE 1: Example of the three patterns of interest established by the hybrid synthetic data generation approach, addressing optimal operational conditions (top), not optimal operational conditions (middle) and critical operational conditions (bottom).

B. ENSEMBLE METHODS FOR ADVANCED PROGNOSTICS

In order to improve the prediction accuracy of single machine learning models, in this research work an ensemble method for prediction is proposed.

Once the synthetic signals are generated, data corresponding to three different operational conditions can be further processed. Some key features, $X_1, \dots, X_m$, are first extrated to learn models that can predict the operational condition Y. This means that for each signal i, we have its observed values for the extracted features $\mathbf{x}_i = (x_{i1}, \dots, x_{im})'$ and its operational condition y_i. The centroid of each operational condition or pattern is considered, $\mathbf{g}_k$, $k = 1, 2, 3$, as well as a distance function in order to measure the similarity between $\mathbf{x}_i$ and the corresponding centroid, $\mathbf{g}_k$, which numerically represents a pattern. For each $\mathbf{x}_i$, the Euclidean distance $D_k(\mathbf{x}_i)$ is computed as $d(\mathbf{x}_i, \mathbf{g}_k) = \sqrt{\sum_{a=1}^{m}(x_{ia} - g_a)^2}$, given that the operational condition of signal i is k and $y_i = k$. Then, for each operational condition k an anomaly threshold is computed based on the furthest observation to the pattern, $th_k = \max_{y_i=k}\{D_k(\mathbf{x}_i)\}$.

Given a new feature vector $\mathbf{x}_{new}$, $D(\mathbf{x}_{new})$ distances are calculated and compared to the aforementioned anomaly thresholds th_k, for each $k = 1, 2, 3$. Then, a degree of belonging to each operational condition or pattern is determined straightforward based on the previously established threshold, th_k, and linearly interpolating the distance $D_k(\mathbf{x}_{new})$ (see Equation 5). That means that if $D_k(\mathbf{x}_{new}) \geq th_k$ the degree of belonging to condition k is 0 and if $D_k(\mathbf{x}_{new}) = 0$ then the degree is set to 100.

$$P_k(\mathbf{x}_{new}) = 100 \left(1 + \frac{-1}{th_k} D_k(\mathbf{x}_{new})\right) \tag{5}$$

for $0 \leq D_k(\mathbf{x}_{new}) \leq th_k$. This degree of belonging is particularly interesting considering the critical condition ($k = 3$).

The key advantage of the proposed approach is the prognostics capabilities of the RUL estimation. First, the different backward and forward time windows to build the time-lagged datasets have been considered. For each time window t the distance to the critical operational condition $D_3(\mathbf{x}_t) = d(\mathbf{x}_t, g_3)$ and the associated degree of belonging $P_3(\mathbf{x}_t)$ have been computed. Then, the training dataset for the machine learning methods of the ensemble are the feature vectors $\mathbf{x}_t$ that were extracted from the signals and the target variable is $D_3(\mathbf{x}_t)$, for the considered time instances t.

In order to exploit the prediction capabilities of different machine learning algorithms, the following methods have been considered in the proposed approach: bagging as a tree learner [26], Support Vector Machines for regression (SVR) as a kernel method [27] and k-Nearest Neighbor (*kNN*) as a similarity-based method [28] [29]. Predictions made by the base learners are combined in a stacking fashion using a Multi-Layer Perceptron (*MLP*) neural network [30].

Before going ahead we introduce the general ideas of the considered learning methods. Bagging (bootstrap aggregation) is an ensemble method itself that grows an ensemble of trees. It employs averaging to improve the predictive accuracy and control over-fitting. The sub-sample size is always the same as the original input sample size but the samples are drawn with replacement (bootstrap), and therefore each instance can be drawn more than once. A large number of trees can be therefore grown. The bagging for regression analysis are an ensemble of different regression trees in which each leaf draws a distribution for the continuous target feature, $D_3(\mathbf{x}_t)$. More precisely, a bagging is a collection of K tree predictors T_{θ_k}, with $k = 1, ..., K$, being θ_k the random parameter vector that determines how the k-th tree is grown. All the predictor features are considered for splitpoint selection at each node. It is assumed that all features and θ_k are independent and identically distributed, and sample individuals are independently drawn from the joint distribution. For a new feature vector, $\mathbf{x}_{new}$, the prediction is the average of the predictions given by every single tree T_θ, as it can be seen in Equation 6.

$$d_{bag}(\mathbf{x}_{new}) = K^{-1} \sum_{k=1}^{K} (T_{\theta_k} | \mathbf{x}_{new}) \tag{6}$$

In the case of SVR, given a margin of tolerance ϵ, the idea is to minimize the error by individualizing the hyperplane that maximizes the margin while keeping in mind that part of the error is tolerated. Given a kernel function, $K(x_t, x_s)$, data is transformed into a higher dimensional feature space to make possible to perform the linear separation. In this study a Gaussian kernel is applied. It can be expressed as $K(x_t, x_s) = exp(-\gamma||x_t - x_s||^2)$, being γ the hyperparameter. The learning process solves the minimization problem: $\min_{\omega,\xi_t} \frac{1}{2}||\omega||^2 + C\sum_{i=1}^{n}(\xi_i - \xi_i^*)$, subject to $(\omega \cdot \phi(x_t) \geq \rho - \xi_i)$ and $\xi_i \geq 0$, and being C the regularization parameter and ϕ the underlying function in the kernel $K(x_t, x_s) = \phi(x_t) \cdot \phi(x_s)$. The problem can be transformed to the dual form by using Lagrange multipliers, α_t, and quadratic programming using the formula $\min_\alpha \frac{1}{2}\alpha' K\alpha$, subject to $0 \leq \alpha_t \leq 1/(\nu n_T)$, $t = \{1, ..., n_T\}$, $1'\alpha = 1$. Then, the function used to predict the distance value, $D_3(\mathbf{x}_{new})$, given the feature vector $\mathbf{x}_{new}$, depends only on the support vectors (see Equation 7).

$$d_{SVR}(\mathbf{x}_{new}) = \sum_{t=1}^{n_T}(\alpha_t - \alpha_t^*)K(x_t, x_s) + b \qquad (7)$$

where b is the bias term.

Following the same schema, the kNN regression method used in this study estimates $D_3(\mathbf{x}_{new})$ given $\mathbf{x}_{new}$ by local interpolation of the distances associated to the k nearest neighbors in the training set, $NN(\mathbf{x}_{new})$. The distance metric used may be the Euclidean distance, or Minkowski distance, $D(\mathbf{x}_t, \mathbf{x}_s) = \left(\sum_{l=1}^{m}|x_{il} - x_{jl}|^{1/p}\right)^p$ among others. More precisely, given $\mathbf{x}_{new}$ the algorithm computes the k closest instances in the training set and outputs the mean of their target values, as it can be seen in Equation 8.

$$d_{kNN}(\mathbf{x}_{new}) = \frac{1}{k}\sum_{t \in NN(\mathbf{x}_{new})} D_3(\mathbf{x}_t) \qquad (8)$$

Once the previously mentioned methods are properly trained they are combined in a stacking fashion by means of a MLP neural network approach. The first step is to fix the structure of network, i.e.: the number of fully connected layers, which is set to 3, and the number of nodes or neurons in each layer. These latter is set heuristically, checking different configurations given a specific dataset and choosing the optimal configuration from a list of candidates. Rectified Linear Units (ReLU, R) are used as non-linear activation functions for each layer, since it is proven that they converge much more quickly and reliably than other activation functions. In order to estimate the unknown parameters of the neural network, namely the weights, $\boldsymbol{w}$, and biases, $\boldsymbol{b}$, backpropagation algorithm and ADAM solver are applied. The weights are recalculated at each iteration of the learning process, from back to front, in order to minimize the error obtained when approximating the given inputs to the desired output by the general formula $\boldsymbol{w} \leftarrow \boldsymbol{w} - \eta\frac{\delta E}{\delta \boldsymbol{w}}$. $E(D_3, \hat{D}_3) = \sum_t^{n_T}(D_3\mathbf{x}_t - \hat{D}_3(\mathbf{x}_t))^2$ is the error function, which corresponds to the mean squared error. The biases $\boldsymbol{b}$ are similarly computed. Once the MLP model is learnt, the outputs of bagging, SVR and kNN, $\boldsymbol{d} = (d_{bag}, d_{SVR}, d_{kNN})$, respectively, are set as inputs for the MLP so that a final prediction is provided (see Equation 9 for a simplified version of the formula).

$$d_{MLP}(\boldsymbol{d}) = b + \sum_{j=1}^{M} w_j R_j \qquad (9)$$

being M the number of neurons at layer h, with $R_j = max(0, z)$ and $z = b_j + \sum_{i=1}^{n} w_{ji}x_i$ for each neuron.

The motivation behind this stacking approach is to take advantage of data-driven methods with different skills and prediction capabilities, and thus considering a wider variety of cases and more diverse trends on data. They can be seen as a mixture of experts sharing their knowledge.

As a final step within the proposed methodology, and given the characterization of a signal in time T (in weeks), a prediction for the distance to the critical condition is obtained, $d_{MLP}(T)$, as well as a related degree of belonging to the critical behaviour $P_3(T)$ similarly as it is mentioned in Equation (5). To do so, the developed ensemble method is trained based on a buffer of previous T weeks. This provides us with the chance of validating and deploying the approach in a real-time condition monitoring platform. Moreover, the deployed predictive models are online fitted to the most recent trends on data once the buffer is established and updated, and the predictions are adapted accordingly for each time horizon.

Furthermore, given horizon time points $T_1, \ldots, T_m$ and the corresponding degree of belonging to the critical working condition $P_3(T_1), \ldots, P_3(T_m)$ a Gaussian curve is fit, with their corresponding μ and σ parameters, $P_3(T) = \frac{1}{\sigma\sqrt{2\pi}}e^{-(T-\mu)^2/(2\sigma^2)}$. This approximation results in a *RUL* estimation in terms of time to failure $T_{failure}$, as it can be seen in Equation 10, and a degree of belonging $P_3(T_{failure})$ that represents the status of the asset over time and the severity of potential critical operational conditions.

$$T_{failure} = \underset{T}{\operatorname{argmax}}\{P_3(T)\} \qquad (10)$$

C. HYBRID SYNTHETIC DATA GENERATION AND ENSEMBLE METHOD APPROACH

The overall algorithm of the proposed hybrid methodology is presented in Algorithm 1 and 2.

IV. EXPERIMENTATION

A. EXPERIMENTAL SETUP

Experiments are performed in real ball bearings, where an acquisition system is connected to generate training and testing data. Ball bearings are the critical essential bodies in different industrial rotation machinery and are greatly affected by defects that can be observed in terms of vibrations. Thus, the defect diagnosis and prognosis methods

Algorithm 1 Synthetic data generation for behavioural pattern extraction

Input: a set of vibrational data from an asset $\mathbf{x}$ and the patterns of interest, G
Output: feature dataset X and distance D_k

```
for k in behaviour of interest G do
    if no data available then
        generate a set of diverse synthetic data x'_i using Equation 1, 2, 3 and 4
        extract features X_j, j = 1, ..., m
    end if
    obtain centroid g_k
    set distance calculation D_k
end for
```

Algorithm 2 Ensemble methods for advanced prognostics

Input: diverse dataset features X and horizon times T
Output: RUL estimation

```
train the models with X in the ensemble model to produce d_T = (d_bag_T, d_SVR_T, d_kNN_T)
train the MLP model using d_T to produce d_MLP_T
for x_new do
    for t ∈ T do
        compute d_bag, d_SVR, d_kNN using Equation 6, 7, 8
        compute d_MLP using Equation 9
    end for
    estimate RUL using Equation 10
end for
```

are very important for the bearing condition monitoring. Even thought there is a wide variety of defects that results in critical failures, this study has been focused in the outer race defect. In Figure 2 it can be seen how a bearing can be subdivided into different components. Each of the components can have defects and produce faults in the system. Figure 2 (b) shows the outer race of the bearing which the failure is studied along this work. Some defects in that race implie that the balls make some jumps when they pass across it. This can be detected in the vibrational data achieved from the bearing.

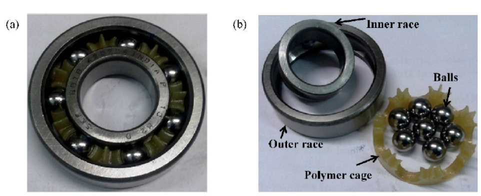

FIGURE 2: Illustration of a ball bearing and its components separately [31]

Bearing data is characterized as mentioned in Section III and classified in 3 main categories: optimal working conditions, not optimal working conditions and critical conditions. As the bearing is working in real operation conditions, stress tests cannot be performed and the values recorded are most of them related to optimal working conditions. Due to this issue, data available is incomplete and the generation of synthetic data is needed.

A sensor reading is acquired every hour, containing a set of up to $16,000$ values, which are related to the vibrational information of the asset. An example of vibrational data can be seen in Figure 3. As mentioned earlier there are no events available regarding critical operational conditions. Taking into account this key issue and the amount of data needed to develop a diverse training set for the predictive models, the number of signals for each operational working condition is set to 3000 by applying the synthetic data generation approach. This data is obtained by applying a physical model and also considering the domain expert knowledge (see Algorithm 1).

Prior to fit the models, raw vibrational data is properly processed to extract a set of features that are representative for the problem to be solved, which is the asset failure detection at early stages of degradation. These features are defined not only in time domain but also in frequency domain as commented in Section II-C. Signal characterization allows reducing the amount of information to be analyzed, minimizing computing and storage efforts and improving model accuracy on unseen data.

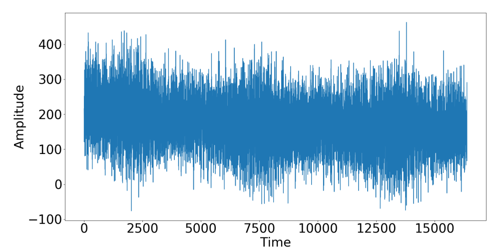

FIGURE 3: Real raw signal illustration for the outer race defect failure under study.

The set of temporal features we considered in this study are listed in Table 1.

Similarly, a set of frequency-domain features are also calculated (see Table 2).

All the features extracted from the time domain and frequency domain are combined to produce a complete feature vector X that represents the health status of the asset under study. A dimensionality reduction method is used aiming at reducing the computational cost associated to all the features extracted from raw signals, and focusing on the relevant information for the problem to be solved. Before applying the data reduction method a normalization between 0 and 1 of each feature is developed, what enables to prevent different weights depending on the feature value scale. In this work, the *Principal Component Analysis* (*PCA*) method is applied, where the number of new components in the transformed feature space is chosen in terms of the variability explained by each component. As a result, a set

Feature	Definition
Root mean square, $RMS(\boldsymbol{x})$	$\sqrt{\frac{1}{n}(x_0^2 + ... + x_{n-1}^2)}$
Peak value, $Pv(\boldsymbol{x})$	$\frac{max(\boldsymbol{x})-min(\boldsymbol{x})}{2}$
Crest Factor, $Crf(\boldsymbol{x})$	$\frac{Pv(\boldsymbol{x})}{RMS(\boldsymbol{x})}$
Average, $\mu(\boldsymbol{x})$	$\frac{1}{n}\sum_j x_j$
Standard deviation, $\sigma(\boldsymbol{x})$	$\sqrt{\frac{\sum_j (x_j-\mu(\boldsymbol{x}))^2}{n-1}}$
Median, $Me(\boldsymbol{x})$	$x_{(n/2)}$, the $n/2$th element once they are sorted
Variance, $\sigma(\boldsymbol{x})^2$	$\frac{\sum_j (x_j-\mu(\boldsymbol{x}))^2}{n-1}$
Kurtosis value, $Kv(\boldsymbol{x})$	$\frac{1}{n}\sum_j \left(\frac{x_j-\mu(\boldsymbol{x})}{\sigma(\boldsymbol{x})}\right)^4$
Skewness value, $Sv(\boldsymbol{x})$	$\frac{1}{n}\sum_j \left(\frac{x_j-\mu(\boldsymbol{x})}{\sigma(\boldsymbol{x})}\right)^3$
Clearance Factor, $Clf(\boldsymbol{x})$	$\frac{Pv(\boldsymbol{x})}{\frac{1}{n}\sum_j(\sqrt{\lvert x_j\rvert})}$
Impulse Factor, $Imf(\boldsymbol{x})$	$\frac{Pv(\boldsymbol{x})}{\frac{1}{n}\sum_j \lvert x_j\rvert}$
Shape Factor, $Shf(\boldsymbol{x})$	$\frac{RMS(\boldsymbol{x})}{\frac{1}{n}\sum_j \lvert x_j\rvert}$
Shannon entropy, $H_t(\boldsymbol{x})$	$-\sum_j p_j \log_2 p_j$
Weibull negative log-likelihood, $WNL(\boldsymbol{x})$	$-\sum_j \log\left((\beta/\eta)(x_j/\eta)^{(\beta-1)}\exp(-(x_j/\eta)^{\beta})\right)$
Normal negative log-likelihood, $NNL(\boldsymbol{x})$	$-\sum_j \log\left(\exp\frac{-(x_j-\mu(\boldsymbol{x}))^2/2\sigma(\boldsymbol{x})^2}{\sigma(\boldsymbol{x})\sqrt{2\pi}}\right)$

TABLE 1: Time domain features extracted from signals, given real data or/and synthetic data.

Feature	Definition
Central frequency, CF	$\frac{\sum_{i=0}^{N} X(i/Nf_s)^2}{\sum \mathbf{x}}$
Root Mean Square, RMS_f	$\sqrt{\frac{\sum_{i=0}^{N} X(i/Nf_s)^2}{\sum \mathbf{x}}}$
Root Variance, RV	$\sqrt{\frac{\sum_{i=0}^{N}(X_i')^2}{4\pi^2\sum_{i=0}^{N}(X_i)^2} - (\frac{\sum_{i=0}^{N}(x_i' x_i)}{2\pi\sum_{i=0}^{N}(x_i)^2})^2}$
Kurtosis value, $Kv(\mathbf{x})$	$\frac{1}{m}\sum_{j=1}^{m}\left(\frac{\mathbf{x_j}-\mu(\mathbf{x})}{\sigma(\mathbf{x})}\right)^4$
Skewness value, $Sv(\mathbf{x})$	$\frac{1}{m}\sum_{j=1}^{m}\left(\frac{\mathbf{x_j}-\mu(\mathbf{x})}{\sigma(\mathbf{x})}\right)^3$
Standard deviation, $\sigma_f(\mathbf{x})$	$\sqrt{\frac{\sum_{j=1}^{m}(x_j-\mu(\mathbf{x}))^2}{m-1}}$
Spectral entropy, H_f	$\sum_{f=0}^{f_s/2} p(f)\log(p(f))$
DTC	$y_k = x_0 + (-1)^k x_{N-1} + 2\sum_{n=1}^{N-2} X_n \cos(\frac{\pi k n}{N-1})$

TABLE 2: Features extracted in the frequency domain for the real and the synthetic data.

of p features or representative principal components for the problem are obtained. These components are a combination of the previous $X = \{X_1, ..., X_m\}$ features.

With all the data in the new principal components space, the centroids representing each working condition pattern $\mathbf{g}_k$, $k = 1, 2, 3$ are defined. This centroid-based representation enables to have a direct diagnosis and it also provides a distance measure over time for *RUL* estimation. A new set of data $\mathbf{x}_{new}$ will be classified based on its closest pattern.

A degradation model is also developed to validate the model in terms of *RUL* estimation. In this case, each synthetic data is generated with the same data generation model applied in data hybrid system. The degradation was obtained modifying the amplitude $A(f_k)$ of the important frequencies S_1 gradually increasing the severity in a realistic linear way from an optimal working condition to a critical state. As explained before, critical data is not recorded due to the fact that the system is in production and the implied consequences would not be affordable. This degradation model is used to validate the evolution of the prognostics obtained by the proposed approach.

Prognostics is designed taking into account the evolution of the degree of belonging P_3 over time which is direcly associated to the distance to the critical condition centroid D_3 as explained in Equation 5. In the case study illustrated here, 5 different time windows, $T = 2, 3, 4, 6, 8$, are considered. These time windows are established to obtain different predictions and to enable an accurate approximation for the *RUL* estimation.

In order to validate the proposed approach, two different evaluation scenarios are envisaged:

- Evaluation metrics during the different phases of the learning process, i.e.: training, validation and test. They are mathematical formulas; e.g.: Mean Squared Error, *MSE*, or Mean Absolute Error, *MAE*. They evaluate how well the model is predicting the target value in time.
- Validation of the method in a simulated degradation scenario, which aims at checking the accuracy of the approach from an optimal condition to a critical degradation stage.

The achieved evaluation results are discussed in the next Section.

B. EXPERIMENTAL RESULTS

The hybrid synthetic data generation presented in III-A was developed to address the lack of relevant data issue. Data acquired from the system was only related to optimal working conditions. The dataset used comprises 465 real signals that were augmented with 2535 synthetic signals in order to have a total of 3000 signals corresponding to the optimal working condition. Similarly, 3000 synthetic signals were generated for each of the two other patterns of interest; i.e.: not optimal working conditions and critical working conditions. As an example, one sample of the signals created in the frequency domain can be seen in Figure 1.

The variability explained by the principal components (PCA) suggested to retain the first 6 principal components (% 94.33 of total variability retained).

Obtained centroids are applied to determine how the system is working on each time instant. Working condition is chosen by determining which centroid is the nearest $D_k(\mathbf{x}_t)$, $k = 1, 2, 3$. In Figure 4 the different distance measurements for real values can be seen. It can be seen that the minimum distances are mainly related to the green ones (optimal working condition) and it is coherent with the fact that acquired real signals are obtained under optimal working conditions. These data provides a health fingerprint that will be applied for *RUL* prediction. A new fingerprint can also be simply classified by using the distance to each centroid. This will be applied as a powerful diagnostic tool in future work.

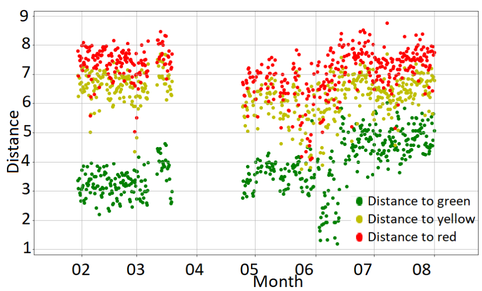

FIGURE 4: $D_k(\mathbf{x}_t)$ distance from each real data to the centroids calculated for each working condition, $k = 1, 2, 3$; green, yellow and red, respectively).

To prevent the system reaching the critical working condition, a set of predictive data-driven machine learning models are developed and combined in a stacking fashion. These methods were presented in III-B and the parameters set for each one are introduced in Table 3. The set of free parameters selected is established by a simple grid search off-line fashion, using the 80% of the dataset in a nested validation framework, i.e.: $2/3$ of the whole training dataset is used for training the models and the remaining $1/3$ is used for validating the free parameters. Once the optimal free parameters are set, which means selecting the ones that best fit the training data, the other 20% of the original dataset is applied for testing the resulting models on unseen data.

TABLE 3: Each model parameters. *parameter values in the considered time windows, $T = 2, 3, 4, 6, 8$ weeks.

Model	Parameters
Bagging	n_estimators*={105,105,95,55,15}
SVR	C*={1,10,10,0.01,10} kernel=Gaussian with γ='scale' ϵ=0.1 penalty='squared l2'
kNN	n_neighbors*={14,7,12,24,2} p=2
MLP	validation split=0.1 epochs=200 batch size=1 activation function='ReLU' solver='ADAM' hidden layer 1*={40, 50, 20, 60, 20} hidden layer 2*={70, 80, 40, 20, 10} hidden layer 3*={20, 1, 10, 20, 10}

The test results obtained by the models are presented in Table 4. As it can be seen, there is no such a model obtaining the best accuracy values for all the time windows considered. Even if some of them seem to be the most accurate for some specific time windows, they are not optimal as a whole. Each time window has its own ideal model. In order to obtain a unique generic model for all the time windows, an ensemble method has been developed as explained in III-B.

TABLE 4: *MSE* results obtained for each proposed method and the ensemble method on each time window.

Model	**Time window**				
	2 weeks	3 weeks	4 weeks	6 weeks	8 weeks
Bagging	0.686	1.008	0.896	0.286	**0.278**
SVR	**0.597**	1.116	0.866	**0.269**	0.311
kNN	0.625	**0.758**	**0.553**	0.300	0.445
MLP	**0.758**	**0.828**	**0.642**	**0.306**	**0.317**

An illustrative example of the results achieved by the models in the ensemble when testing them on unseen data is presented in Figure 5. It can be seen that the predictions given by the resulting models are similar to the real data, which implies that all of them are able to successfully model evolving trends on the health condition of the asset over time.

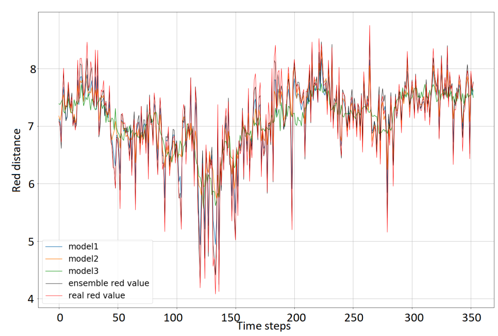

FIGURE 5: Comparison between the predictions given by the models used in the proposed approach and the real values with a time window of 2 weeks. Model 1, 2 and 3 stands for bagging, SVR and kNN, respectively, while the ensemble method red value is referred to the prediction given by the MLP.

The synthetic degradation trend is generated for a more detailed validation of the approach for advanced prognostics under . The distances to the critical working condition pattern D_3 over time are presented in Figure 6.

Let the dashed vertical orange line in Figure 6 be the initial time t_i, and the dashed vertical blue line be the training time t_t and the distance $D_3(\mathbf{x}_t)$ where t is the time considered. For each time window T, the models are trained and the optimal parameters are set with the data $D_3(\mathbf{x}_t), t = [t_t - T : t_t]$. Validation of the ensemble method is obtained by predicting the distances to the centroid $D_3(\mathbf{x}_t)$ for each T. Results are exposed in Table 5 and 6. In Table 6 the degree of belonging P_3 is provided instead of the distance D_3 which appears in Table 5. Evaluation results are obtained for each time window and the absolute error is also computed. It can be seen that the lowest absolute error (0.337) is the one associated to the largest time window case (8 weeks), which also requires a big amount of data. This could imply a computational problem and it must be taken under consideration carefully. The 4 weeks time window case also obtains a good accuracy (0.383) and it reduces the computational cost.

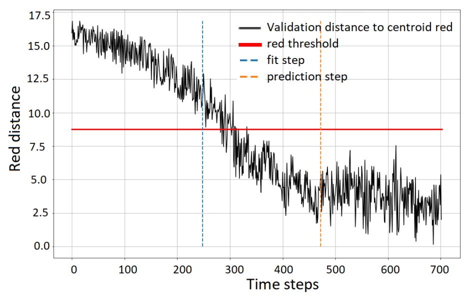

FIGURE 6: Synthetically generated degradation pattern which is applied for validation of the proposed approach in terms of *RUL* prediction.

TABLE 5: Validation results. Real vs predicted distances D_3 and computed error in the considered time windows *TW* (weeks).

TW	Real dist.	Predicted dist.	Absolute error
2	7.173	9.288	**2.115**
3	6.451	6.863	**0.411**
4	5.543	5.926	**0.383**
6	3.904	4.802	**0.898**
8	2.822	3.160	**0.337**
Mean absolute error			**0.829**

TABLE 6: Validation results. Real vs predicted degree of belonging P_3 and computed error in the considered time windows for critical working condition.

TW	Real degree	Predicted degree	Absolute error
2	18.034	0.0	**18.034**
3	26.278	21.561	**4.716**
4	36.653	32.286	**4.367**
6	55.391	45.129	**10.262**
8	67.739	63.877	**3.861**
Mean absolute error			**8.247**

A Gaussian approximation is developed for results presented in Table 6 which represents the degree of belonging to the critical working condition in terms of time. Approximation is made separately to real and predicted degree of belonging $G_{real}(\mu, \sigma)$ and $G_{pred}(\mu, \sigma)$. Each curve has its own shape and *RUL* estimation is made according to the time t when the degree of belonging has the maximum value $max(P_3)$. Comparison between real and predicted data is presented in Table 7, where predicted time to failure, degree of belonging and standard deviaton are presented. There is a very low absolute error between real model and the prediction obtained by the model, namely 0.281 in term of *RUL*. Absolute error percentage is calculated to evaluate the resulting accuracy, as follows:

$$\frac{(8.596 - 8.315)}{8.596} 100 = 3.26\% \tag{11}$$

3.26% represents a very small percentage and therefore we can assume that a very accurate model is obtained. Table 7 also presents the real and predicted values and the absolute error for standard deviation and the degree of belonging in the highest point. Results achieved are in concordance with the real values.

TABLE 7: RUL estimation results. Real vs predicted time to critical operational conditions and prediction certainty in terms of the Gaussian distribution parameters, $G(\mu, \sigma)$, that approximate the curve of real and predicted distance values in the considered time windows.

	Real	Predicted	Absolute Error
RUL (weeks)	8.596	8.315	**0.281**
Standard deviation, σ	4.060	3.285	**0.775**
Degree of belonging, P_3	68.383	63.056	**5.327**

V. CONCLUSIONS AND FUTURE WORK

This work presents a novel hybrid approach for synthetic data generation, which enables addressing the lack of relevant signals associated to events of interest. This hybridization is implemented by combining real and synthetic data, which is generated on the basis of available literature and domain expert knowledge. This hybrid synthetic data generation process provides a valuable solution in those cases in which real not optimal and critical working conditions are very difficult to obtain since they are not affordable. Generated patterns are consistent with real values studied in this research work and the data reduction and diagnosis developed provides good accuracy on the real data available.

The lack of diverse and relevant data representing behaviours of interest is an important pending issue in many data-driven, industrial scenarios. The main reason is the high economic impact implied by the resulting breakdowns. In this study, a methodology based on the available literature is proposed, providing a proper solution as it can generate signals that are very similar to the real ones acquired from the system during real operation. Moreover, this methodology can be easily applied to any system or failure by adapting the synthetic data generation process and fitting the ensemble method to new trends on data.

Another key advantage of the proposed approach is the developed ensemble prediction system. Three different machine learning models were implemented in an online fitting-based *RUL* estimation and none of them was accurate enough for every considered time window, and thus a fusion of all of them was proposed in an stacking fashion to optimally address this issue. This ensemble method was validated on a synthetically generated degradation trend. It was demonstrated that the prediction accuracy obtained with the proposed approach was very close to the degradation dataset values a good failure predictor. It is also worth mentioning that this approach can highly support maintenance decisions and industrial processes management by providing an easy to use and to understand solution for asset maintainers, designers and data engineers. Moreover, the developed methodology enables the system to evolve from currently applied corrective and preventive maintenance strategies to a more realistic operation-based predictive maintenance.

Future work for this study will include a more complex asset and process characterization with more sensors for the prediction system, aiming at improving the prediction accuracy and the inferred knowledge about the process under study. The presented hybrid methodology will also be applied to other assets and components and other industrial processes, involving different failure modes and and more sources of information towards a cognitive maintenance strategy.

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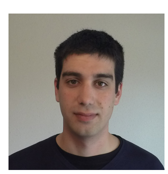

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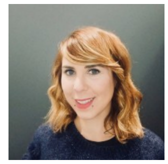

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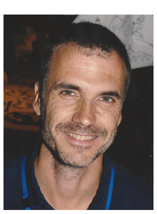

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