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Analysis of Human-Related Incidents during Dynamic Positioning Operations

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Abstract: Dynamic positioning systems ensure additional position accuracy in different operations in the maritime industry, such as shuttling, drilling, diving, pipe laying, and others. Although they are known to be robust systems, they are not exempt from failures leading to incidents, among which we can find human-related incidents. This research analyzes 62 human-related dynamic-positioning incidents and aims to determine which segment in the dynamic positioning system influences these occurrences by applying binary logistic regression modeling techniques in the test sample and validating the results using a control sample. The results indicate that thrusters have the most significant influence on human-related incidents; however, not all DP operations are affected in the same measure. By stratifying the database and considering the different operations in progress, it is noted that human-related incidents while drilling operations are in progress are effectively influenced using a higher percentage of thrusters online.

Keywords: dynamic positioning; human-related incidents; offshore; drilling

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1. Introduction

Dynamic positioning (DP) systems have been used in the shipping industry since the 1970s. Their many advantages have made this system a valuable asset in the offshore industry.

Loss of position, also known as excursion, could happen during operations and constitutes the main risk in any DP operation. Therefore, the DPO (Dynamic Positioning Operator) should react rapidly and try to correct or mitigate the outcome of any such incident [1]. Although high safety standards are in place, incidents in the offshore industry are not uncommon due to problems in the dynamic positioning system. The International Marine Contractors Association (IMCA) receives reports from their associates and publishes them yearly to provide an extra tool for the learning process.

In these reports, the incidents are classified depending on the main cause, and sometimes, a second cause is pointed out to provide extra information. Other important data are provided in order to detail the incident properly.

These reports proved to be helpful, and the reported incidents and near misses are used for updating risk analysis and management [2]. Research using this approach has been reported by Parhizkar et al. [3] and Rebello et al. [4], among other authors.

All the data influencing a particular incident are usually referred to as precursor data. When analyzing a database, a specific pattern exists that could be used to predict an incident. This assertion is the principle behind the regression modeling technique used in this paper. Different authors have recently used the regression modeling method to predict and prevent incidents in the transportation industry. For instance, in road transportation, logistic regression modeling was applied to detect traffic incidents [5] and their duration [6]. This statistical approach has been used to predict human-related incidents in the aviation sector [7,8], which is always suggested as being closely connected to maritime research regarding safety.

Although there are only a few publications concerning the use of logistic regression modeling for predicting incidents in the maritime sector, the ones existing show the advantages of using such a method. Hogenboom et al. [1] explained the influence of humans on maritime incidents with the methodology of regression modeling, while Boullosa-Falces et al. [9] also applied regression modeling for the variable selection process before constructing a prediction model. Furthermore, Weng et al. [10] researched the likelihood of human error occurrence using multinomial logistic regression; the model obtained predicts major accidents in shipping based on meteorological conditions. Dujmović et al. [11] analyzed injector failures onboard drillships, employing the maintenance concept adjustment and design (MA-CAD) method. Fiskin et al. [12] analyzed the variables leading to tugboat accidents using logistic regression.

The Human Element

Knowing that maritime systems are based on people [13], several publications have dealt with different techniques and tools to discern the human element in accidents. The human element is part of any maritime accident investigation, as mentioned by the Marine Accident Investigators' International Forum [14] and the IMO [15]. The following studies are only an indication of the range of methods and not an exhaustive literature review.

Ma et al. [16] proposed a method for analyzing maritime accidents, applying the Hierarchical Holographic Modeling (HHM) approach to identify the most probable human errors based on a survey of maritime experts. The results show that the most probable human errors were related to communication, decision making, situational awareness, and task execution. The authors also found that the frequency and impact of these errors varied across different types of vessels and operations.

Zhang et al. [17] proposed a method called Human Factor Analysis (HFA) based on a complex network to analyze the human factors involved in gas explosion accidents. The HFA method is designed to identify the critical human factors contributing to accidents and provide guidance for safety management.

Park et al. [18] presented a simulation experiment to investigate the navigators' errors in a ship collision in South Korea. The results showed that the navigators' errors were primarily due to their misjudgment of the other ship's speed and course, inadequate communication between the bridge team members, and insufficient training on collision avoidance procedures.

Recent research by Ren et al. [19] presents an exhaustive review of human errors influencing safety, with a focus on the offshore industry. Chen et al. [20] identify fatigue and inexperienced behavior in offshore drilling operators.

In dynamic positioning operations, the human component strongly influences any operational failure [21], as the DPO must regain control when a DP system fails. Although procedures are in place for such events, operators' skills and seamanship are essential for adapting and optimizing procedures to facilitate the return to a normal situation [22].

Human factors in DP incidents were analyzed by Chae [23] using a Bayesian network, and later on, the same author [24] determined the nature of human failure by applying formal safety assessment to these variables and proposing some mitigating measures. Furthermore, Overgard et al. [22] researched different levels of situational awareness of human elements during DP incidents. Subsequently, Dong et al. [25] consider that combining human-related and organizational and technical failures is the base of the majority of accidents during offshore loading operations; the methodology used for concluding this includes an event-and-cause diagram, change analysis, and barrier analysis. Although Bayesian networking is widely applied in DP incident analysis, it is observed to be biased when using the factors for measuring the associated risk, as it generally depends on the best perceptiveness of the person completing the analysis [26]. Therefore, the authors chose to follow the binary regression modeling technique, which different authors have applied to define patterns that could explain a given variable's existence.

Sanchez-Varela et al. [27] proposed a method to determine the odds of incidents caused by humans during dynamic positioning drilling operations. The authors collected data on incidents and associated human causes during drilling operations and used statistical techniques to identify the factors contributing to incidents caused by humans. The only factor identified was the percentage of thrusters online, with incidents caused by humans being more likely to occur when the percentage of thrusters online was low.

The main objective of this paper is to analyze different weather and system configuration variables that might be associated with human-related incidents, finding a mathematical expression that can describe the likelihood of an incident during DP operations being caused by humans. By identifying the variables associated with an incident being caused by humans, the riskiest situations can be pinpointed, and thereby, steps can be taken to improve the safety of DP operations.

2. Materials and Methods

2.1. Database Description

The original database consists of 552 incident reports from the information presented in the event trees of annual DP station-keeping incidents by the International Maritime Contractors Association (IMCA) published from 2007 to 2015 [28–37]. The IMCA DP station-keeping reports are considered the most complete in the oil and gas industry in terms of the number of reports included and the completeness of the information given. However, after 2015, IMCA changed the annual DP station-keeping incidents reports and published only some of the event trees. Due to the large number of cases obtained and the fact that IMCA considered that only a representative sample would be shown each year starting in 2015, the research carried out with these data can be deemed relevant for today's technology advancements.

From the information presented on those event trees, all the different aspects and variables of the incident were recorded in a table. Some of these cases lack information for different variables, so after eliminating cases with missing values, 311 cases remain. The different variables obtained are presented in Figure 1.

IMCA classifies the causality of the incidents into nine different categories. The main causes can thus be computer problems, electrical failures, environmental and weather issues, external causes, human contribution, power failures, reference systems problems, sensor causes, or thruster problems. All the cases have been assigned a main cause, and some can additionally present a secondary cause.

The following information is collected for the incidents: main cause, secondary cause, and main operation in progress.

The statistical distribution of the different main causes is shown in Table 1.

Table 1. Distribution of main causes for DP incidents 2007–2015 (n = 311).

Main Cause	Frequency	Percentage
Computer	50	16.1
Electrical	9	2.9
Environmental	22	7.1
External	5	1.6
Human	40	12.9
Power	48	15.4
Reference	34	10.9
Sensors	14	4.5
Thruster	89	28.6
Total	311	100.0

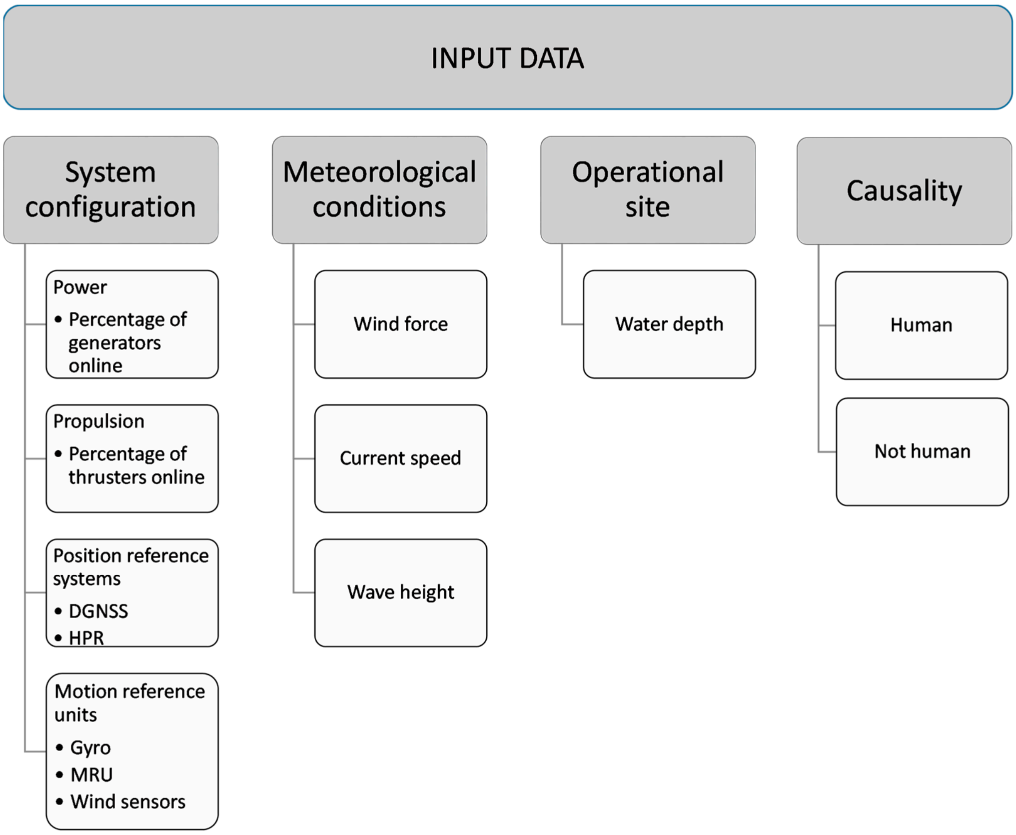

Figure 1. Variables obtained from the IMCA event tree information are classified according to their role during DP operations.

In 78 cases (25% of the overall sample), a secondary cause was defined. Table 2 shows the distribution of different secondary causes, and it is visible that humans are behind most of the incidents where a secondary cause was determined (23 cases, 29.5%).

Table 2. Distribution of secondary causes for DP incidents 2007–2015 (n = 311).

Secondary Cause	Frequency	Percentage
Computer	5	6.4
Electrical	13	16.7
Environmental	4	5.1
External	6	7.7
Human	23	29.5
Power	10	12.8
Reference	6	7.7
Sensors	5	6.4
Thruster	6	7.7
Total	78	100.0

An incident is human-related when either the main cause or the secondary cause has a human nature. According to this statement, the database contains 62 incidents (20% of the total) cataloged as having a human cause (one of the incidents had human contribution as either main or secondary causes). Also, the operations in progress when the human-caused incident occurred are shown in Figure 2. Drilling operations are identified in 19 cases (30.6%), followed by Remote Operated Vehicle (ROV) operations (11 cases, 17.7%) and cargo operations (10 cases, 16.1%), diving (8 cases, 12.9%), and cable/pipe lay operations (7 cases, 11.3%). The rest of the operations, FPSO (floating production storage and offloading), seabed, shuttle, Stby (standby), topside works, transit, and trenching, have only one case.

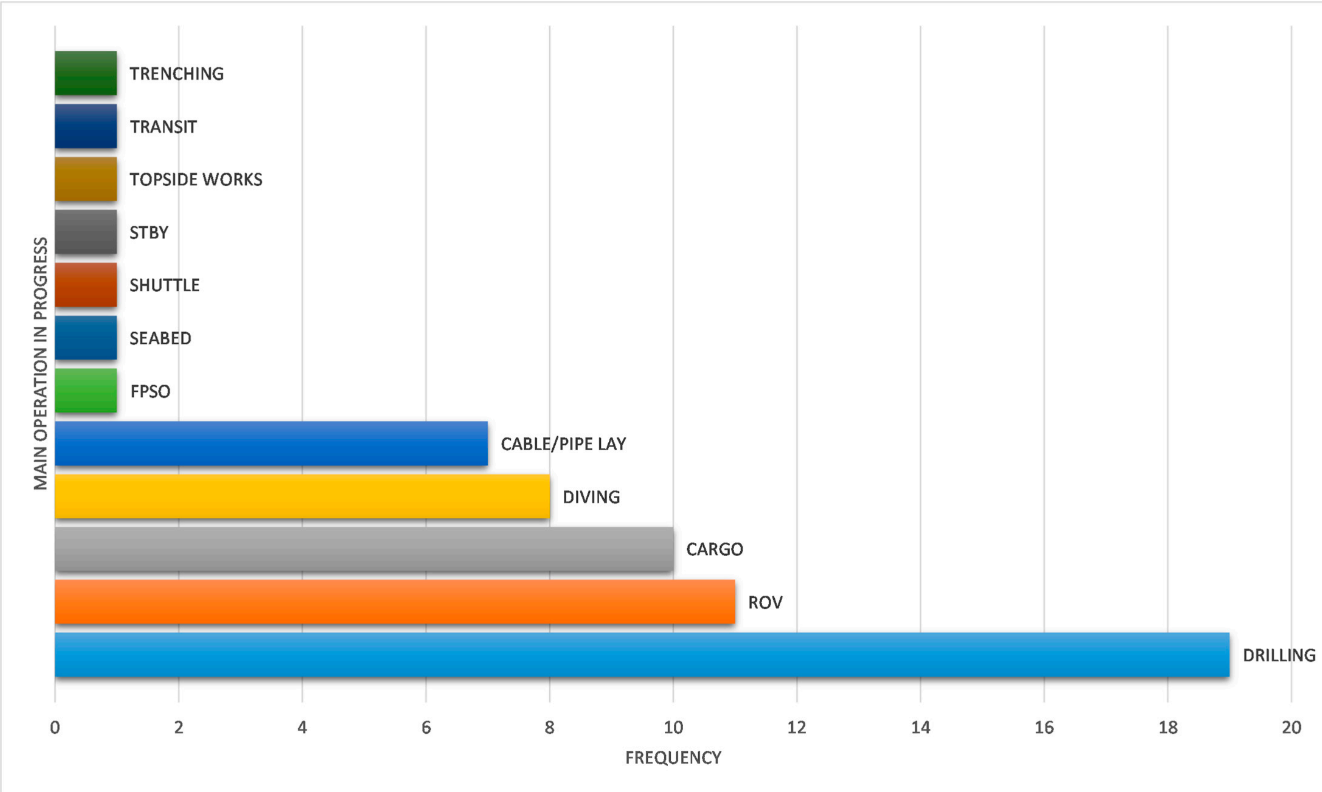

Figure 2. Distribution of the main operations in progress when a human-related incident occurred (n = 62).

The independent variables included in this research are shown, along with a brief description, in Table 3.

Table 3. Independent variables included and their description.

Variable	Description
Water depth	Indicates the water depth in meters at which the operations are taking place
Percentage of thrusters	The number of thrusters online divided by the total number of thrusters, both online and standby
Percentage of generators	The number of generators online divided by the total number of generators, both online and standby
GNSS	The number of Differential Global Navigation Satellite Systems (DGNSS) systems selected in the DP system
HPR	The number of hydroacoustic position reference (HPR) systems selected in the DP system
Gyros	The number of gyros in use during the DP operations
MRU	The number of motion reference units (MRUs) in use during the DP operations
Wind sensors	The number of wind sensors in use during the DP operations
Wind force	The force in knots of the wind blowing when the incident occurred
Current speed	The speed of the current in knots when the incident occurred
Wave height	The significant wave height in meters
Human cause	When an incident is human related, the variable takes the value 1. If any other parameter causes the incident, the variable takes the value 0
Main operation in progress	The operation was in progress when the DP incident occurred

2.2. Binary Logistic Regression Modeling

Binary logistic regression modeling is a statistical procedure to analyze and compute the connection between a dependent variable (outcome) and one or more independent variables (predictors). The logistic regression modeling methodology involves several important steps for ensuring accurate and reliable results [38]. An overview of the process is shown in Figure 3.

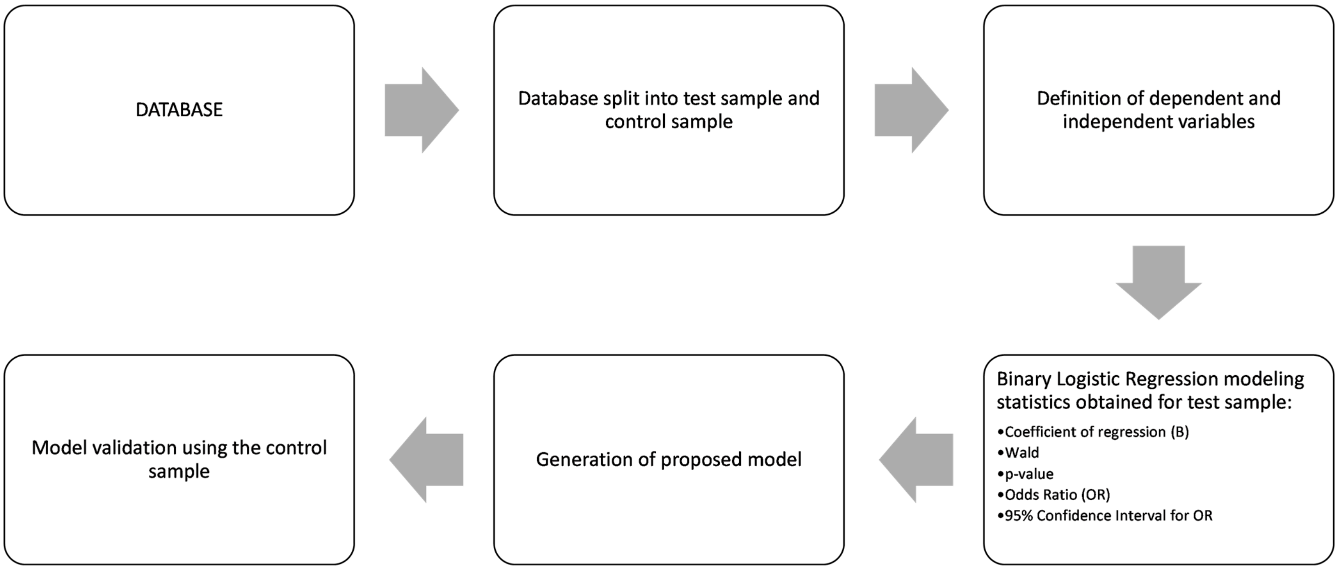

Figure 3. Overview of the steps followed in the research using the binary logistic regression modeling methodology.

The regression modeling methodology tries to find a pattern within a set of variables that could predict the likelihood of whether or not a dependent variable will happen. In our research, this dependent variable is human cause, which can take the values 0 or 1 as per the explanation in Table 3.

After this, the data are prepared for analysis. This analysis involves checking for missing values, outliers, and other data quality issues and making necessary corrections. The data are also formatted to suit logistic regression analysis, with the dependent and independent variables clearly identified.

Next, exploratory data analysis is conducted to understand the relationships between the variables and identify any potential problems or limitations of the data. This exploratory analysis involves creating scatterplots, histograms, and other visualizations and calculating summary statistics and correlations between the variables.

At this point, the database is split into test and control samples. Both samples will have the same distribution for the dependent variable human cause.

The regression modeling then takes the independent variables from the test sample and checks whether they contribute to creating a model that could have a good prediction for the likelihood of the dependent variable happening or not.

The model for determining whether or not an incident has a human-related cause is given as follows:

$$Z = B_1X_1 + \ldots + B_kX_k + B_0 \tag{1}$$

where Z represents the linear predictor function to determine the human nature that caused the incident; $X_1, \ldots, X_k$ represent each independent variable, k being the number of independent variables; and $B_0, B_1, \ldots, B_k$ represent the regression coefficients to be estimated.

The independent variables are selected to enter the model equation using the Enter method. The variable is selected to enter the equation depending on the *p*-value and the confidence intervals (CIs).

The likelihood P of an incident having a human cause in a specific case is given by the following:

$$P = 1/(1 + \exp(-Z)). \tag{2}$$

P has a value comprehended between 0 and 1; for values close to 0, the probability of having a human cause becomes lower, and for values close to 1, the probability of having a human-related incident is higher. P is then calculated for each case, and then the case is classified into one of two groups: no human cause (0) if $P < 0.5$ and human cause (1) when $P > 0.5$.

The model's goodness of fit is evaluated using measures such as the R-squared value and residual plots.

2.3. Model Validation

Obtaining an equation that defines the model is not the final step. The model needs to be validated by applying it to the control sample.

The likelihood P as per Equation (2) is applied for each case of the control sample, and the results are assigned to one of the groups: no human cause (0) when $P < 0.5$ and human cause (1) when the likelihood $P > 0.5$.

It must be validated to determine whether the proposed model's prediction is accurate. The validation is carried out on the control sample by comparing the actual cause of each case incident with the predicted value obtained from the model. If there is a match, that is, if both values match, then it is considered that the proposed model has the capacity to make good predictions.

The goodness of fit is assessed by verifying how probable the results obtained are for the proposed model. This check compares the number of cases belonging to the second group (human cause) with the number expected if the model were valid. When the number of correctly classified cases is high, the model is expected to have good prediction power.

The error E is obtained by comparing the observed probability (P observed) and the estimated probability (P estimated) as follows:

$$E_i = P\ \text{observed}_i - P\ \text{estimated}_i \tag{3}$$

This error E_i takes values in the span of $(-1, 1)$. E_i will be zero when both the estimated and the observed cause are human. The goodness of fit is evaluated by studying the dispersion of the model's errors.

Afterward, the regression analysis results are interpreted, considering both statistical and practical significance. The regression model coefficients are interpreted in the context of the research question, and any model assumptions are checked and justified.

3. Results

3.1. Descriptive Statistics

A total of 311 cases are included in the analysis, with every variable having valid data for each case. Among these cases, 62 incidents (19.9%) have a main or secondary human-related cause.

Table 4 describes each independent variable estimated to affect the cause of the incident and is, therefore, considered a candidate for the model.

Table 4. Descriptive statistics of the different variables studied ($n = 311$).

Variables	Mean	Standard Error	Median	Standard Deviation	Minimum	Maximum
Water depth (m)	706.24	44.476	200.00	784.350	10.0	2838.0
Percentage of thrusters	93.80	0.706	100	12.432	50	100
Percentage of generators	70.94	1.242	66.67	21.865	33.33	100

Table 4. *Cont.*

Variables	Mean	Standard Error	Median	Standard Deviation	Minimum	Maximum
No. of DGNSS	2.17	0.043	2.00	0.756	0	4
No. of HPR systems	0.62	0.042	0.00	0.740	0	3
No. of taut wires	0.21	0.028	0.00	0.496	0	2
No. of lasers	0.26	0.026	0.00	0.462	0	2
No. of fan beams	0.00	0.003	0.00	0.057	0	1
No. of RADius	0.01	0.006	0.00	0.113	0	1
No. of microwave radars	0.09	0.017	0.00	0.304	0	2
No. of inertia systems	0.02	0.009	0.00	0.160	0	2
No. of gangways	0.00	0.003	0.00	0.057	0	1
No. of artemis	0.01	0.006	0.01	0.098	0	1
No. of gyros	2.90	0.023	3.00	0.402	1	4
No. of MRUs	2.56	0.032	3.00	0.570	1	4
No. of wind sensors	2.46	0.036	2.00	0.631	1	4
Wind force (knots)	13.76	0.483	12.00	8.497	1	55
Current speed (knots)	1.14	0.061	0.90	1.065	0.0	7.0
Wave height (m)	1.47	0.073	1.00	1.276	0.1	10.0

The incidents happened while the vessels were performing a different range of operations. Figure 4 shows the distribution of the incidents by main operations, indicating the percentage of the incidents with a human-related cause against the incidents that did not have a human cause. There are some operations in which there are no incidents with a human origin, for example, anchor handling (three incidents), approaching (two incidents), construction (two incidents), jacking (one incident), personnel transfer (seven incidents), rock dumping (one incident), and trials (seven incidents).

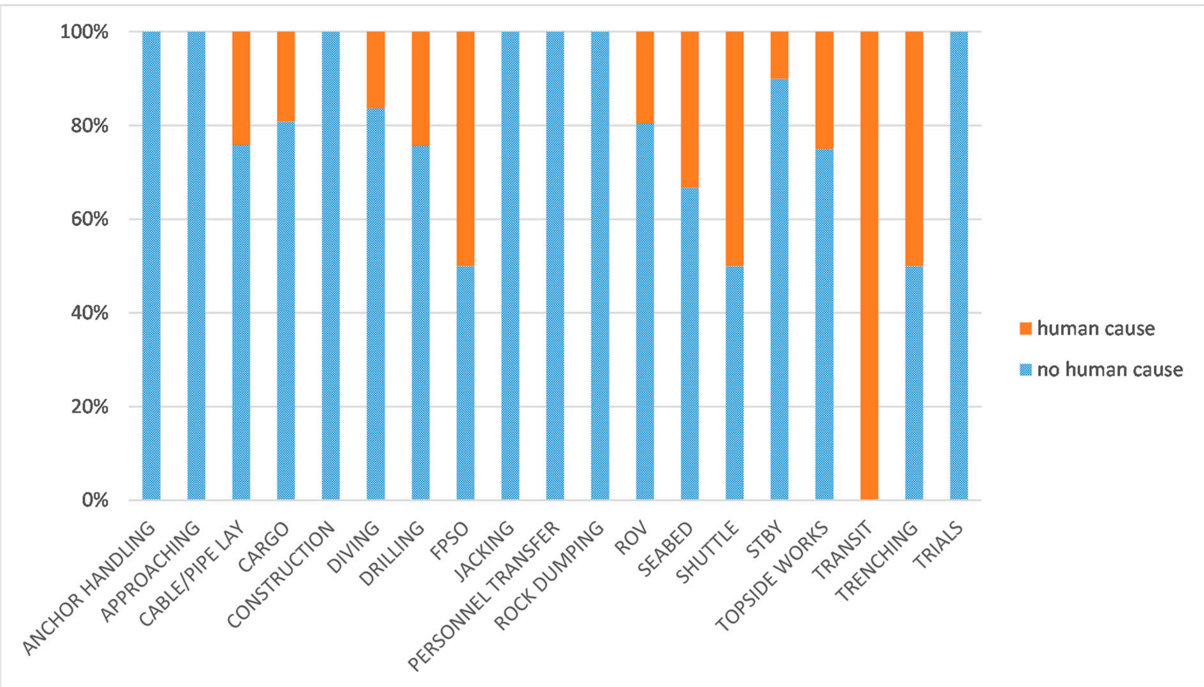

Figure 4. The percentage of incidents having a human cause is represented for each operation in progress.

For the rest of the operations, transit is the one where all the incidents had a human cause. FPSO, shuttle, and trenching operations had 50% of the incidents with a human-related cause. For the rest of the operations, the percentage of human-related incidents varied between 10% and 33%.

The first step in this research is to analyze the distribution of each variable according to whether they have a human-related cause or not. As can be seen in Figure 5, there are no significant differences in the distribution, except for the variable percentage of thrusters shown in (b). In this case, the incidents have a human cause if the percentage of generators is below 100%. In contrast, the cause of the incident is not human related if the percentage of thrusters online equals 100%.

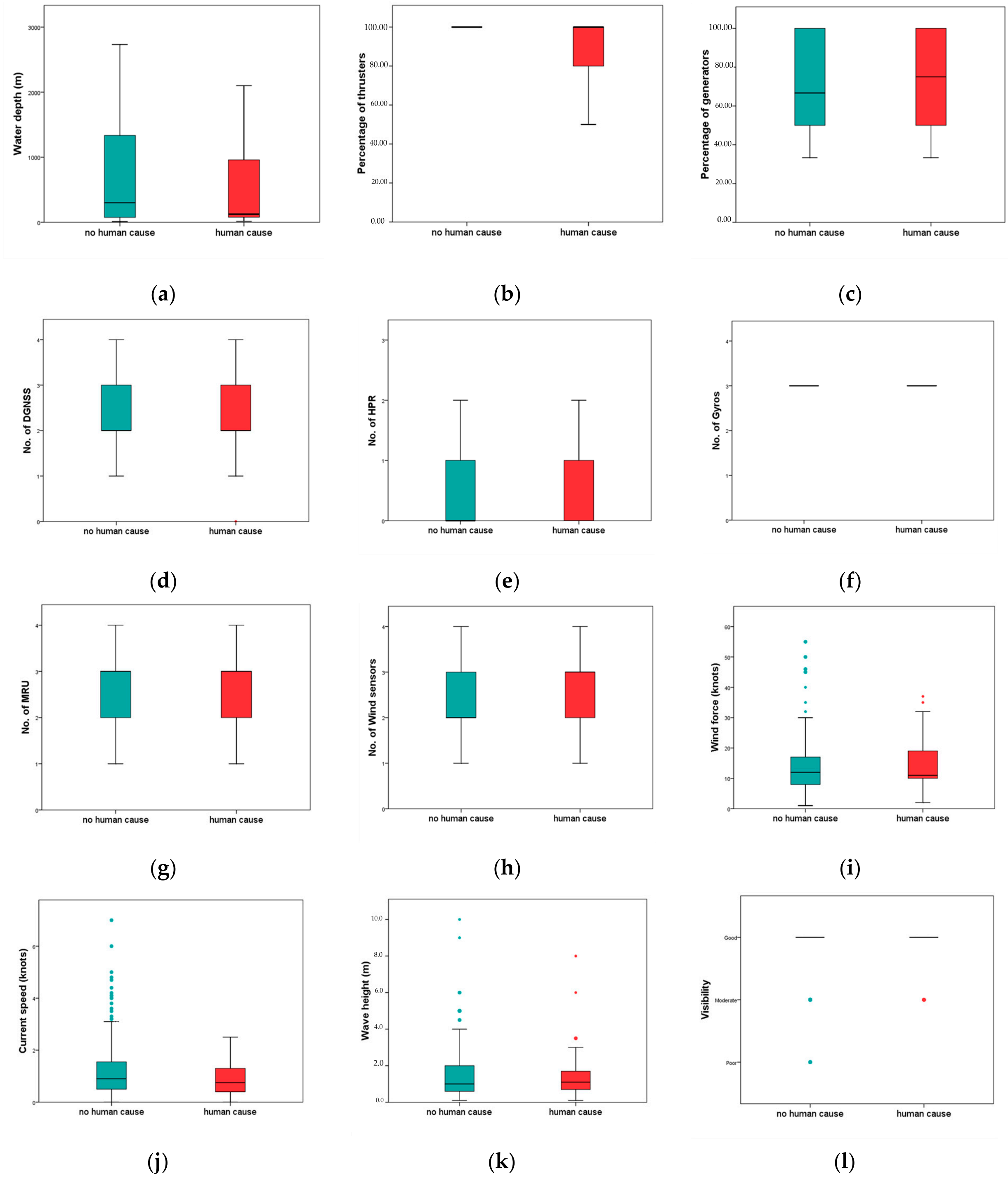

Figure 5. Distribution of the potentially relevant variables stratified by whether the incident had a human-related cause or not: (**a**) water depth, (**b**) percentage of thrusters, (**c**) percentage of generators, (**d**) GNSS, (**e**) HPR, (**f**) gyros, (**g**) MRU, (**h**) wind sensors, (**i**) wind force, (**j**) current speed, (**k**) wave height, and (**l**) visibility. (n = 311).

3.2. Test Sample

The initial database is split into the test sample and the control sample. The distribution of the variable human cause follows a similar distribution for both samples. The test sample has 162 cases, of which 129 (79.6%) had no human cause, and 33 (20.4%) were human-related.

Firstly, the independent variables are entered into the model individually to ensure their significance. The results obtained from this are shown in Table 5, and at this stage, the variables considered significant are water depth and percentage of thrusters. However, the B statistic of the variable water depth equals zero, meaning the influence of this variable in the eventual model is null. Therefore, only the variable percentage of thrusters will be considered when defining the model using the Enter mode.

Table 5. Individual results of each variable when the binary regression model (method: Enter) is performed, with human cause being the dependent variable. (n = 162).

					95% CI for OR	
Causal Factor	**B**	**Wald**	***p*-Value**	**Odds Ratio (OR)**	**Lower**	**Upper**
Water depth	0.000	1.186	0.2760	1.000	0.999	1.000
Percentage of thrusters	−0.031	5.337	0.021	0.970	0.944	0.995
Percentage of generators	0.013	2.104	0.147	1.013	0.995	1.031
DGNSS	0.318	1.464	0.226	1.375	0.821	2.303
HPR	−0.056	0.044	0.833	0.945	0.561	1.595
Gyros	0.400	0.507	0.477	1.492	0.496	4.489
MRU	0.824	4.880	0.027	2.279	1.097	4.734
Wind sensors	0.199	0.465	0.495	1.220	0.689	2.160
Wind force	0.011	0.163	0.687	1.011	0.959	1.065
Current	−0.349	2.3021	0.129	0.705	0.449	1.107
Wave height	−0.162	0.523	0.470	0.850	0.548	1.319

As per these results, the percentage of thrusters is the only variable with a p-value of less than 0.025 and does not include the number 1 in the confidence interval. With this in mind, the model is created using the variable percentage of thrusters, using the Enter method, which is defined by the following equation:

$$Z = 1.489 - 0.031 \cdot \text{percentage of thrusters}. \quad (4)$$

3.3. Model Validation

The model proposed in (3) is applied to the control sample to validate the model. The control sample consists of 149 cases, of which 120 (80.5%) had no human cause and 29 (19.5%) had a human cause.

By applying the equation described in (2), the likelihood of each incident having a human cause is calculated, and the errors are calculated according to (3). The error distribution is shown in Figure 6.

The model can accurately classify 120 cases (81%). It is observed that the proposed model correctly classifies 100% of the incidents without a human cause; however, the model does not correctly classify any of the human-related incidents. In this sense, the overall number of correctly predicted incidents is 249 of 311 (80.1%).

The proposed model can be practically applied by calculating the likelihood of the different percentages of thrusters online, as shown in Figure 7. The probability of an incident being initiated by humans decreases as the percentage of thrusters rises.

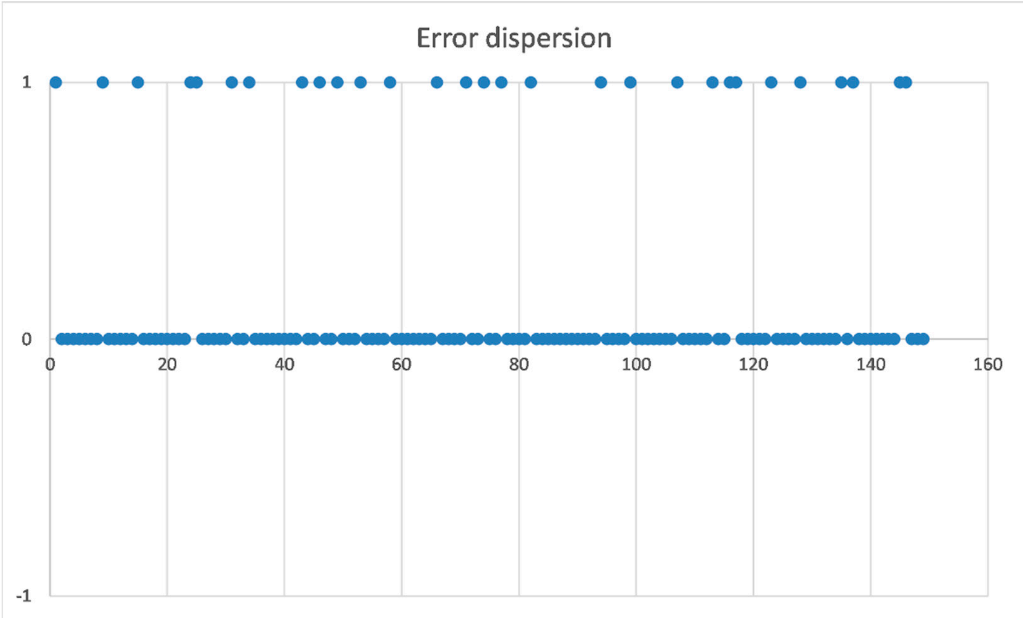

Figure 6. Distribution of the errors found during the model validation, where 0 shows no error, 1 indicates an incident incorrectly classified as caused by humans, and −1 indicates an incident incorrectly classified as no human cause.

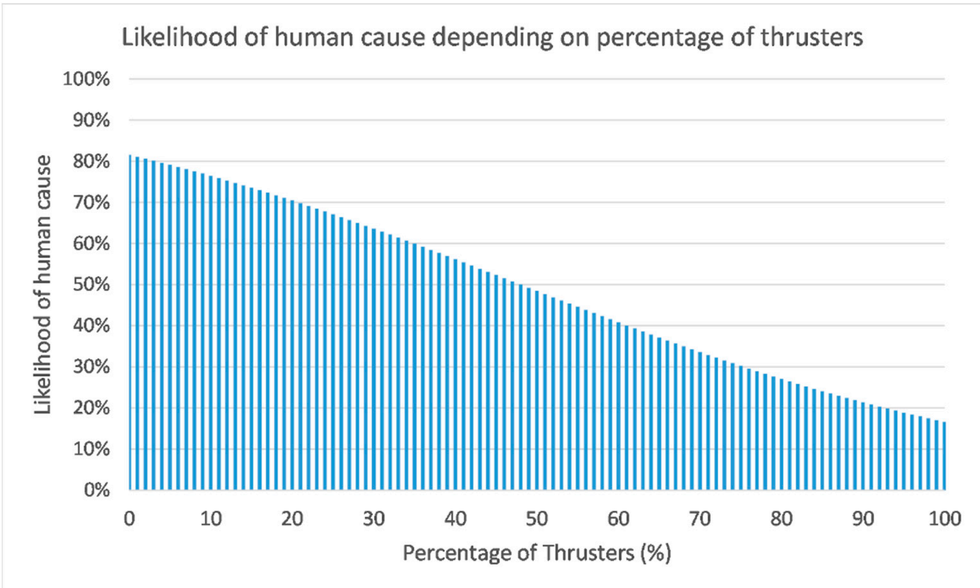

Figure 7. The likelihood of an incident being caused by humans, according to the proposed model, for the whole range of percentages of thrusters.

Considering only the incidents in which a human element was related to the cause, the distribution of the variable percentage of thrusters stratified by the main operations in progress is shown in Figure 8. There is a bigger range in the distribution of the drilling operations, which is at the operations having the bigger frequency for incidents. Cable/pipe laying and diving clearly have a percentage of thrusters that tends to be below 100%. ROV and cargo, on the contrary, maintain the percentage of thrusters at the maximum level, while some exceptional cases lower this value. The rest of the main operations only present one case and are not considered significant in this research.

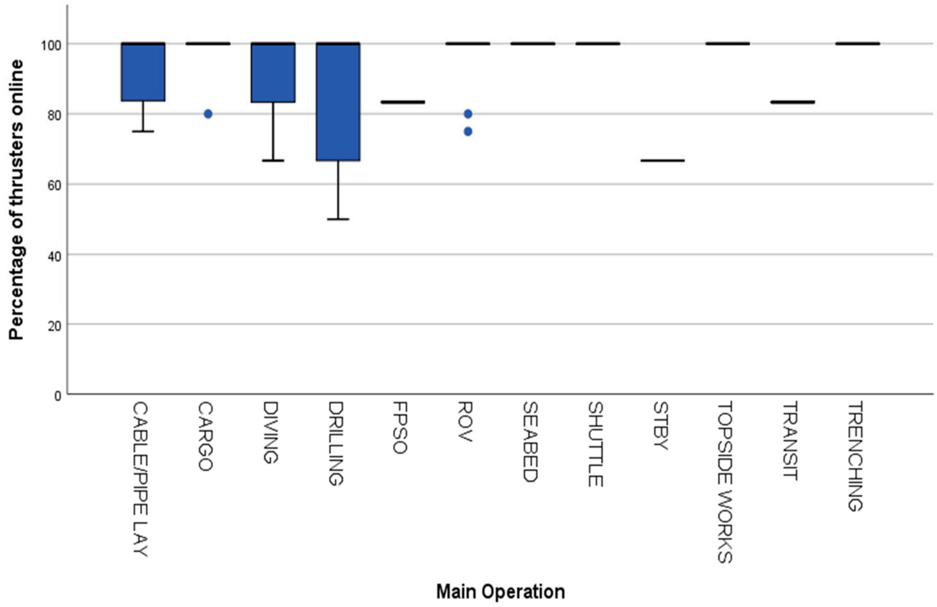

Figure 8. Distribution of the variable percentage of thrusters online stratified by main operations in progress. (n = 62).

4. Discussion

This paper's main objective was to find a model that could predict when a DP incident has a human cause based on different independent variables related to DP configuration and weather.

Human-caused incidents mainly result when individuals do not follow the established procedures after a loss of position occurs. It is a common practice for the DPO to take manual control of the system in the event of an incident. It seems reasonable to suppose that a large number of thrusters online could help reduce the loss of position, thus responding faster and having better situational awareness when taking over the control. However, there could be other reasons for human-related incidents, such as inappropriate design of the human–machine interface, as perceived in some of the cases (for example, due to bad design, the DPO accidentally pressed the wrong button).

The database contained 311 incidents, which were considered significant for obtaining results through binary regression modeling. Of all the variables, only the percentage of thrusters was considered to enter the model equation.

However, the model validation showed that the equation could poorly predict the incidents with a human cause. In contrast, the proposed model perfectly predicted all the incidents without human cause.

Limitations of this Study

It is clear that in this research, the database studied comprises DP incidents occurring while different DP operations were in progress. The configuration of the DP system is different on each occasion, and it is not the same as the need for a drilling platform, which needs to stay stationary in a position, as the configuration is required for ROV operations and the vessel needs to follow up a predefined route. According to this explanation, the results differ from those of Sanchez-Varela et al. [27] for drilling operations. Although the same independent variable, the percentage of thrusters, is considered in the model, the equation defined for DP drilling operations is more robust than the one presented in this paper. This assertion is also supported by the results shown in Figure 4, where it can be seen that the distribution of the variable percentage of thrusters has a bigger range. Therefore, the equation will explain the human causes with a better fit.

Moreover, the model follows the same rule as the one for DP drilling operations, where the bigger the percentage of thrusters, the bigger the possibility of having a human-caused incident.

All of the above indicates that the modeling should be stratified by the main operation in progress. This stratification poses another problem, as the different operations also have a different number of incidents, which, in some cases (transit, trenching, construction), is insufficient to perform a logistic regression. The source of data on incidents does not provide a complete list of all the incidents happening during DP operations, as there are several external and internal factors influencing the reporting, as defended by Psarros et al. [39] and Kongsvik et al. [40].

This research is built on a sample of 311 incidents. DP operations are known to have outstanding safety measures; therefore, the incidents during such operations are the exception. However, for this reason, the available data are limited, and the results should be taken with caution.

Owing to Øvergård [41], the sample presents incidents only due to the lack of records of non-incidents (i.e., events that worked as planned). This issue was also pointed out by Hollnagel [42], warning about considering incident reports only instead of studying successful outcomes, which would lead to learning how to succeed under varying conditions. However, the successful incidents are rarely worth reporting, and thus the results presented are biased by this selection, showing only part of all operations carried out.

It is assumed in regression modeling that the connection between the independent variables and the dependent variable is even; that is, it follows a given pattern—this may be positive or negative, linear or non-linear, but is uniform over the whole array of values. According to this, the coefficients shown in the proposed model should be used with prudence.

The predictive capacity shown by the model should also be considered with caution, as the cases correctly classified were the ones without a human cause. This conclusion leads to the determination that the model is not yet ready to be applied in the industry and that further research should be performed.

5. Conclusions and Future Research

It can be concluded that human-related incidents while using DP are influenced by the percentage of thrusters configured in the DP system. However, not all operations are affected in the same measure and should be researched in the future using a larger database to corroborate the results provided in this paper.

The technological advancements of the last years, related to manning, operational, and environmental or technological factors, are missing from this research. Thus, in a future research line, comparing the sample from this paper to another future sample will give interesting conclusions.

Another interesting line for future research would consider different regression methods for comparative analysis.

Furthermore, future research should focus on the use of thrusters online with other operational limitations, including environmental issues.

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