Identifying Factors of Dynamic Positioning Incidents through Association Rule Mining

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Accidents in the offshore industry can have severe repercussions for people, cargo, vessels, and the environment, making maritime safety a crucial concern. Dynamic positioning incidents, particularly those involving loss of position, represent a significant risk. This study employs association rule mining to analyze DP incident data, leveraging its strength in discovering robust associations. Using the Apriori algorithm, the analysis identifies strong association rules for loss of position (drift-off, drive-off) and loss of redundancy situations. The findings reveal event-related variables and potential causal relationships, providing insights and guidance for reducing the risk and occurrence of future DP incidents through stringent and targeted safety measures.

KEY WORDS
~ Dynamic positioning incident
~ Data mining
~ Apriori algorithm
~ Association rule mining
~ Offshore
~ DPO

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1. INTRODUCTION

Dynamic Positioning (DP) systems play a pivotal role in the offshore industry by automating vessel position and heading control. The offshore oil and gas sector significantly impacts national energy security and economic stability, making reliable DP systems essential. These systems are installed on offshore vessels engaged in DP operations, which may occasionally experience loss of position (LoP) incidents. While DP system is hailed as a technological boon, ensuring vessels maintain specific positions and headings automatically; they still require vigilant monitoring by certified and competent Dynamic Positioning Operators (DPOs).

The importance of analyzing DP incidents and identifying probable causal links cannot be overstated. This study thoroughly investigates the causes of DP incidents using association rule mining, specifically employing the Apriori algorithm within the Weka software developed by the University of Waikato.

The primary objective of this paper is to identify the main causes contributing to DP incidents through a statistical analysis followed by the Apriori algorithm and association rule mining. The study utilizes data from the International Maritime Contractors' Association (IMCA) database and annual reports on DP incidents, which collectively offer a comprehensive collection of 1352 incidents and undesired events over the period from 2004 to 2021. This research reveals strong association rules, investigates potential interactions between components, and provides solutions and recommendations to reduce the number of DP incidents.

Research on dynamic positioning (DP) incidents remains limited, with only a few studies providing statistical analyses. Current research on maritime accidents predominantly focuses on human factors and specific ship types. Techniques such as the Analytical Network Process (ANP) and the Human Factor Analysis and Classification System for Maritime Accidents (HFACS-MA) have been employed to examine these factors (Akyuz, 2017; Chen et al., 2013), highlighting the significant role humans play in marine accidents.

Additionally, location-specific studies examine marine accidents in particular regions. Raiyan et al. (2017) used Event Tree Analysis (ETA) to show how combined factors can cause accidents. Erol et al. (2018) used neuro-fuzzy methods to investigate accidents in the Strait of Istanbul. Ozaydin et al. (2022) proposed a hybrid model combining Bayesian Network (BN) and Association Rule Mining (ARM) to analyze marine accidents, revealing minimal requirements for fishing vessel accidents. Weng and Li (2019) examined contributory factors in 66 shipping accidents in Fujian waters.

In the realm of DP incidents, Ismail et al. (2014) used descriptive statistics to analyze 219 incidents, emphasizing the importance of crew training, discipline, and continuous maintenance. Overgard et al. (2015) studied critical incidents during DP operations, providing insights into the human factors involved such as situational awareness and decision-making of DPO. Hauff (2014) used Bayesian belief network analysis to investigate LoP incidents. Azad (2014) presented a criticality analysis of platform supply vessels, identifying potential DP accident causes. Chae (2017) applied formal safety assessment (FSA) techniques to human errors and accidents involving DP vessels.

Pil (2018) investigated the causes of DP system malfunctions, identifying control and feedback systems as main contributors to propulsion system failures. Olubitan and Loughney (2018) conducted a statistical analysis of DP-related incidents from 2000 to 2016, revealing an increase in incidents during spring and summer, with Diving Support Vessels (DSVs), pipe lay, and drill ships involved in the most incidents. Reference and thruster systems were the leading causes.

Sanchez et al. (2021) used binary logistic regression modeling to predict LoP incidents during drilling operations, calculating the probability of deviations from desired positions. Chae and Jung (2015) examined 612 LoP incidents from 2001 to 2010, identifying PRS errors as the leading cause, followed by DP computer, power system, human error, and thruster systems.

Few studies have focused on strong association rules for DP incidents. This study aims to fill that gap by examining factors contributing to DP incidents, such as loss of position (LoP) and loss of redundancy (LoR) incidents. It provides specific rules and valuable insights into the relationships between these variables, potentially enhancing safety measures in DP vessel operations.

2. METHODOLOGY

2.1. Association Rule Mining Analysis

Association rule mining (ARM) is an effective method for identifying significant relationships concealed within large datasets. To understand the causes and effects of DP incidents and the relationships between antecedents and consequents, ARM was applied using Weka open-source machine learning software. These relationships are typically defined by strong association rules. Through this study, preventive measures can be developed to reduce the number of DP incidents by relying on strong association rules that highlight the factors contributing to those incidents.

The Apriori algorithm, integrated into the Weka program, was employed for association rule mining. Weka, a comprehensive machine-learning workbench, provided a user-friendly interface for dataset analysis. The Apriori algorithm, first introduced by Agrawal and Srikant (1994), is one of the most recognized and widely used algorithms in this domain. Its primary objective is to generate association rules characterized by high confidence levels, which indicate the accuracy and reliability of the rules. Apriori is used to uncover complex associative relationships between factors, extracting frequently occurring patterns from large datasets to identify common item sets and associations among different item sets. By revealing these relationships, the study aims to inform the development of preventive measures to mitigate DP incidents effectively.

While the method provides valuable insights due to its flexibility and simplicity, it also presents notable computational challenges and limitations. Practical application requires careful interpretation and consideration of dataset characteristics, threshold settings, and computational resources.

An analytical description of the association rule can also be defined in the form (Agrawal and Srikant, 1994);

$X \Rightarrow Y$, where $X, Y \subseteq I$, $X \cap Y = \varnothing$. The association rule $X \rightarrow Y$ suggests that the occurrence of Y is dependent on the occurrence of X. In the context of association rules, X is referred to as the antecedent, representing the item(s) that precede the occurrence of other item(s) denoted as Y, which is known as the consequent.

The support of the association rule $X \Rightarrow Y$ reflects the probability that item X and item Y happen together simultaneously (in the entire data set). The support of an association rule is quantitatively defined as the ratio of the number of transactions in the entire dataset that contain both $X \cup Y$, to the total number of transactions in the dataset. This may be mathematically represented as:

$$\text{Support } (X) = \|\{t \in D \mid X \subseteq t\}\| / \|\{t \in D\}\|$$

$$\text{Support } (X \cup Y) \geq \text{minimum support (threshold)}$$

Support is the frequency of occurrence. In example, if the support is 20%, (x) and (y) occur together in 20% of the cases.

The confidence of the conditional probability that item Y will happen on the condition that item X happens. It is called conditional probability. This may be mathematically represented as:

Confidence (X⇒Y) = support (X∪Y) / support (X)

Confidence (X∪Y) ≥ minimum confidence (threshold)

Figure 1 provides a comprehensive summary of the methods used to calculate support and confidence values.

$$support(X \rightarrow Y) = \frac{|\{b_i | b_i \in X \wedge b_i \in Y\}|}{\sum_{i=0}^{m} b_i}$$

$$confidence(X \rightarrow Y) = \frac{support(X \cup Y)}{support(X)}$$

Figure 1. Analytical description of support and confidence (Source: Cakir et al., 2021)

Since there are a great number of these association rules that meet the criteria of support and confidence, filtering and ranking of found rules are provided by the 'lift' factor. Lift displays the confidence of the rule to the past likelihood of subsequent, and it is the result of dividing rule confidence by rule support. It is used to measure the importance of a rule. The lift of an association rule can be shown in the form of:

Lift (X⇒Y) = support (X∪Y) / (support (X) support (Y))

Generally, the higher the lift results, the stronger the association between the items. The result of the lift factor is supposed to be higher than 1. When the lift value is equal to 1, it indicates that there is no association of between variables X and Y. When the lift value exceeds 1, it indicates a positive correlation between variables X and Y. However, in the event that the lift value remains below 1, it indicates the presence of a negative association between the elements, suggesting that they are unlikely to occur together.

The user specifies a minimal support threshold, denoted as *min_sup,* and a minimum confidence threshold, denoted as *min_conf,* before conducting the process of association rule learning. The set of item sets with a support value greater than or equal to the minimal support threshold, referred to as "a frequent item" or large itemset, is denoted as *Lk*. It represents the collection of all frequent k-item sets.

The association rule learning process consists of two distinct stages. In the initial phase, the algorithm identifies all the frequent item sets that possess a support value that is higher or equal to the specified minimum support threshold, denoted as *min_sup*. During the second step, the system produces association rules, computes their confidence levels, and selects association rules that have a confidence level that is higher or equal to the specified minimum confidence thresholds, denoted as *min_conf*.

The Apriori algorithm is a well-established method used in the field of data mining for the purpose of identifying frequent item sets in association rule mining. The technique employs an iterative approach known as layer-by-layer search, where k-item sets are utilised to investigate (k+1) items. Firstly, the algorithm identifies a collection of frequently occurring 1-itemsets. The set is represented by the symbol L1. L1 is used to identify the collection of frequent 2-itemsets, denoted as L2, and subsequently, L2 is utilised to discover L3, and this process continues iteratively until the frequent k-item sets can no longer be ascertained.

Conviction is further employed as a metric to assess the degree of independence between variables X and Y. The concept of conviction involves assessing the likelihood of event X occurring independently of event Y by comparing it to the observed frequency of event X occurring without event Y. In contrast to the confidence metric, conviction considers both X and Y and consistently assumes a value of 1 when the corresponding items are entirely unconnected. Therefore, if the conviction value is 1 or close to 1, it is understood that X and Y items are completely unrelated.

2.2. Workflow of Association Rules Learning on DP Incidents

Workflow for association rule learning on DP incidents encompasses several key stages: data preparation and cleaning, rule modeling, frequent itemset creation, and the generation and analysis of strong association rules comprise the association rule learning process for DP incidents (Huang and Shenping, 2019), as shown in Figure 2.

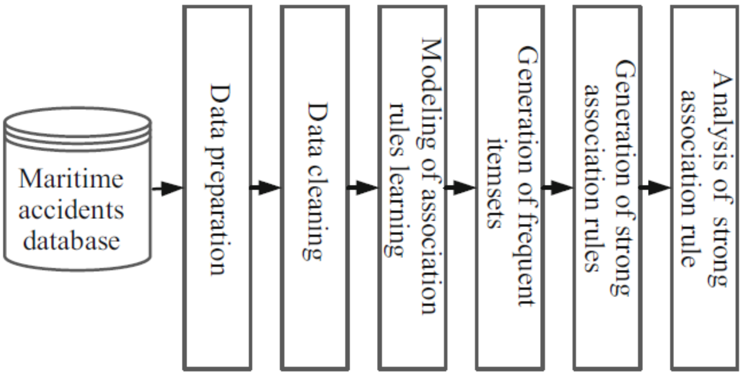

Figure 2. Association rule learning process for DP incidents (Source: Huang et al., 2019)

2.2.1. Data Collection and Preparation

Data collection and preparation involve three main stages: data selection, data processing and data transformation. The data used in this study were sourced exclusively from the IMCA, which is the primary organization that collects and shares records of DP incidents. This reliance on IMCA data represents a limitation, as it excludes data from other potential sources that might offer a broader perspective on DP incidents. Consequently, the findings are based solely on the dataset provided by IMCA, which may not fully encompass all incidents occurring within the industry. This limitation should be considered when interpreting the results and conclusions of this study.

The technique of data pre-processing involves the removal of missing data as well as the generation or deletion of duplicate records. The primary objective of data transformation is to identify and extract meaningful features from the dataset, aligning with the specific goals of the work at hand, in order to effectively portray the data. The IMCA database provided a dataset comprising 1,352 DP incidents that occurred between 2004 and 2021. This was examined and sorted according to the primary cause and incident year. The categorisation is highlighted in Table 1.

Incident \ Year	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	Total
Computer	1	8	4	18	22	8	6	14	8	6	13	13	15	17	22	9	16	28	199
Electrical	1	4	6	5	10	10	12	3	4	0	0	1	0	5	3	5	2	1	70
Environment	2	3	4	4	3	2	4	5	2	3	2	11	0	4	1	3	8	5	59
External Factors	0	0	1	1	1	0	1	0	2	0	2	0	1	2	1	0	1	1	13
Human factor	6	5	13	7	5	10	3	3	11	7	7	10	16	3	9	4	7	0	120
PRS	12	5	9	13	27	17	21	8	6	13	9	6	7	9	13	11	8	20	182
Power	8	4	8	11	9	13	5	7	6	13	9	10	15	10	15	23	33	21	191
Sensors	0	0	0	0	0	1	0	1	5	2	3	5	0	2	5	0	2	1	26
Thruster Propulsion	4	7	3	8	21	12	2	13	20	20	26	24	24	21	37	39	43	53	320
Mechanical	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1
Undetermined	0	0	0	0	1	2	0	0	0	0	0	0	0	0	0	0	0	0	3
Procedures	0	0	0	0	2	0	2	0	0	0	0	0	0	0	0	0	0	0	4
Total	34	36	48	67	102	75	56	54	64	64	71	80	78	73	106	94	120	130	1352

Table 1. Main causes of DP incidents occurred between 2004-2021 (Source: IMCA, 2022)

As evidenced in Table 1, the data indicates that thrusters/propulsion failures have been the primary cause since 2012. Secondly, computer and power-related incidents have been identified as other significant main causes. Furthermore, empirical evidence demonstrates a gradual increase in the overall number of DP incidents during the last decade. Furthermore, Figure 3 illustrates the trend for the main causes of DP incidents over the last 18-year period (2004 to 2021).

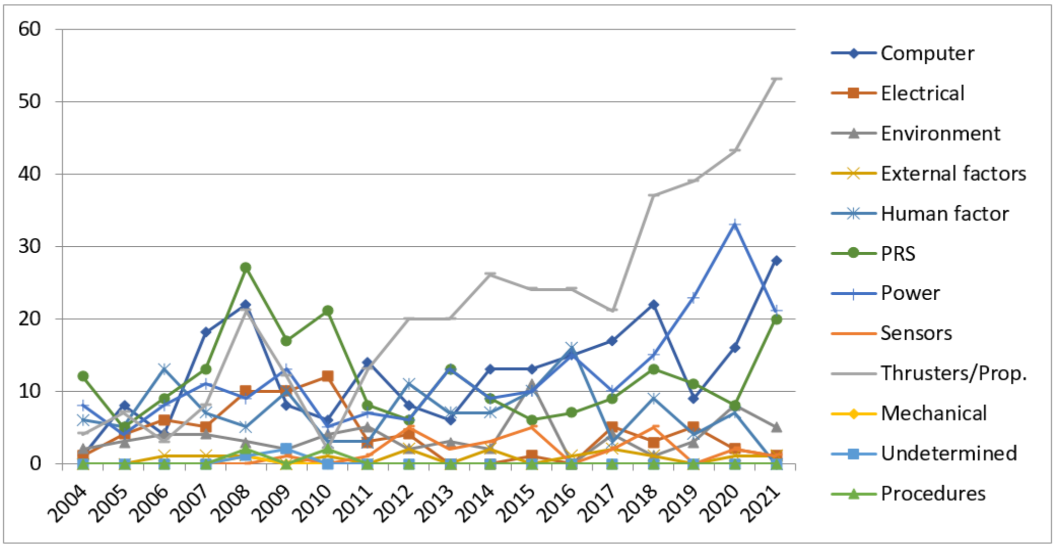

Figure 3. Trend for the main causes of DP incidents between 2004 and 2021. (Source: Authors, 2022)

Table 2 provides a comprehensive overview of DP incidents, categorized by the type of ship and operation, from 2004 to 2021. The data indicate that DP incidents predominantly occur during specific types of operations. The highest percentage of incidents is attributed to diving operations, at 17.3%, followed closely by drilling operations at 16.4%. Additionally, Remotely Operated Vehicle (ROV) operations constitute a significant portion of DP incidents, with 14.6%.

Type of Ship/Operation	Number of Incidents	Percentage (%)
Diving	130	17.3%
Drilling	123	16.4%
ROV	110	14.6%
Cargo	94	12.5%
Pipe lay	58	7.7%
Stand by	42	5.6%
Offshore Load/Offtake	39	5.2%
Cable lay	20	2.7%
Other	136	18.1%

Table 2. DP incidents as per operation type (between 2004 and 2021). (Source: Authors, 2022)

Cargo operations are responsible for 12.5% of the incidents, highlighting their substantial role in the overall distribution of DP incidents. While pipe lay operations are less frequent, they still represent a notable 7.7% of the incidents. Other types of operations, including stand-by operations (5.6%), offshore load/off take operations (5.2%), and cable lay operations (2.7%), contribute smaller percentages to the total number of incidents.

Lastly, a diverse range of other operations collectively accounts for 18.1% of DP incidents. This distribution underscores the variability and complexity of DP operations across different types of ships and operational contexts. The data suggest that while certain operations like diving and drilling are more prone to DP incidents, all types of DP operations require careful monitoring and risk management to mitigate potential incidents.

The attributes selected for this analysis are crucial for understanding DP incident causes and contexts. Each record includes several attributes that describe various aspects of the incidents. The attributes used in this analysis are shown in Table 3.

Attributes	**Explanation**
Root cause	The trigger factors (variable root causes)
Secondary cause	Contributing factors that may have exacerbated the incident (Table 1)
Main cause	The main cause of incident (Table 1)
Incident type	The nature of incident; (LoP (drift-off, drive-off), LoR)
PRS usage	Information about the use of different source type of PRS during the incident; (Yes/No)
Ship/Operation type	Type of DP vessel or operation at the time of incident (e.g., diving, drilling, ROV operations)

Table 3. Attributes utilized in Weka for ARM (Source: Authors, 2022)

2.2.2. Data Cleaning

The IMCA database contains a substantial volume of data, some of is incomplete or duplicate, which impedes its use for analysis. To enhance the accuracy of the association rules, missing or duplicate data were removed. After filtering, 752 DP incidents with sufficient data were identified for further analysis. The Apriori algorithm was applied using 691 attributes, ensuring data integrity and appropriate algorithm settings. A summary of DP incidents is shown in Table 4.

Loss of Position (LoP) incidents (385)		Loss of Redundancy (LoR) incidents (367)
Drift off	Drive off	LoR (367)
324 (%84)	61 (%16)	(%48)

Table 4. Summary of DP incidents (Source: Authors, 2022)

2.2.3. Modelling of Association Rules Learning

A causation model of DP incidents has been developed, incorporating key factors such as main and secondary causes, root causes, incident type (drift-off, drive-off, LoR), PRS usage, and operation type. The analysis model of DP incidents is presented in Figure 4.

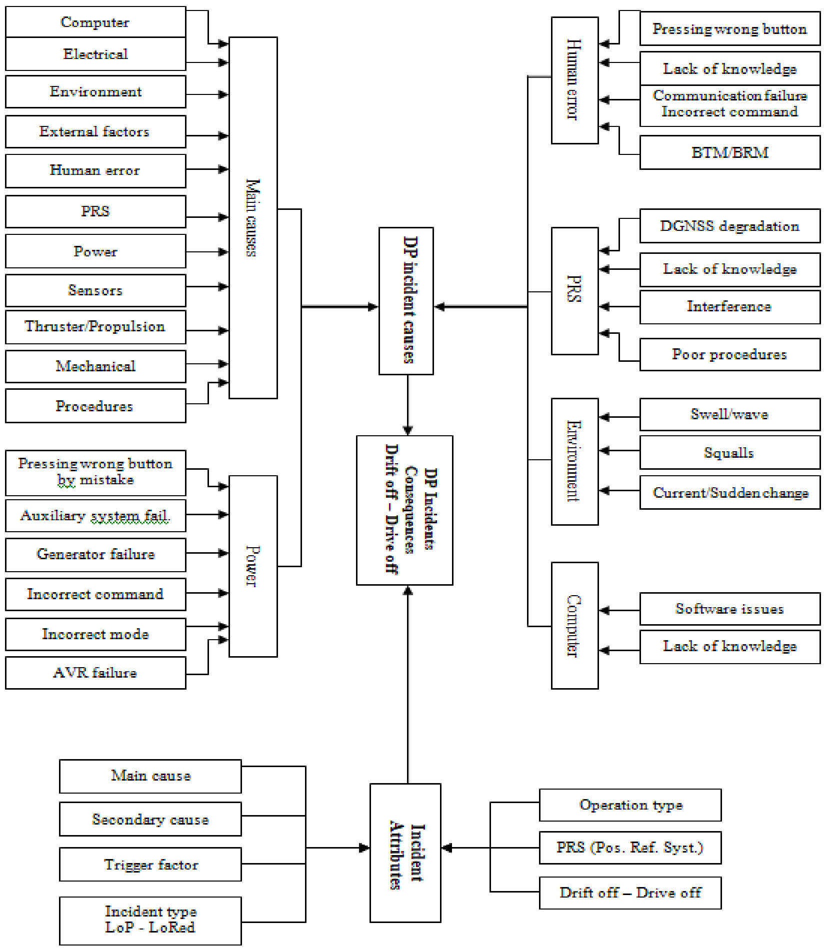

Figure 4. Association rule analysis model of DP incidents (Source: Authors)

2.2.4. General of Frequent Item Sets

The initial step involves generating the candidate set Ck, which comprises items that could become frequent item sets. Support values are calculated for these candidate sets to determine the frequent itemset Lk.

2.2.5. Generation of Strong Association Rules

Association rules are constructed from frequent item sets based on user-specified minimum confidence levels. Strong association rules are those that exceed these thresholds. In this study, the minimum support level was set to 10%, and the minimum confidence level to 60%.

3. ANALYSIS AND DISCUSSIONS OF STRONG ASSOCIATION RULES

Analyzing DP incident data using association rules allows for a quantitative examination of individual accident causation factors and attributes while addressing the challenge of uncovering multi-factor associations-something that traditional mathematical analysis methods often struggle with. The identified strong association rules are examined to highlight their internal connections with DP occurrences and incident causes.

This method effectively resolves the complex task of multi-factor connection mining, allowing for the precise and scientific excavation of relationships between DP incident causation factors and attributes. The findings are objectively presented in the further section.

This section presents the strongest association rules and their relevant points. Tables 5, 6, 7, 8, and 9 display the strong association rules for potential DP incidents, showing the antecedents (on the left-hand side) and consequents (on the right-hand side), based on the highest confidence values. In the Weka Apriori algorithm calculations, a total of 691 attributes were employed to maintain data integrity and adhere to the algorithm's settings.

Table 5 provides a broad overview of general causes and their impact on incidents, illustrating the strongest association rules for DP incidents. This demonstrates the causal relationship between antecedents, such as secondary and root causes, and consequents, including main causes and incident types. This analysis identifies the root causes that trigger the main factors in the occurrence of DP incidents.

Rule	Antecedent	Consequent	Confidence	Lift	Conviction
1	Root_Cause= Feedback failure	Main_Cause= Thruster/Prop	1.0	3.65	31.22
2	Root_Cause= Thruster trip	Main_Cause= Thruster/Prop	1.0	3.65	29.04
3	Root_Cause= DGNSS degraded	Main_Cause= PRS	0.96	5.68	12.48
4	Sec_Cause= Software failure	Main_Cause= Computer	0.86	6.12	5.28
5	Main_Cause= Environment	Drift off	0.81	1.9	2.7
6	Root_Cause= Control system failure	Main_Cause=Thruster/Prop	0.77	2.8	2.84
7	Main_Cause= Human factor	Drift off	0.76	1.78	2.23
8	Sec_Cause= Human factor	Drift off	0.74	1.74	2.12
9	Sec_Cause= Electrical failure	LoR	0.74	1.51	1.87

Table 5. Strong association rules (1) for DP incidents (Source: Authors)

Rule 1 indicates that feedback failures are strongly associated with thruster/propulsion issues, with a confidence of 1.0, a lift of 3.65, and a conviction of 31.22, implying a very reliable rule. Similarly, Rule 2 shows that thruster trips also invariably lead to thruster/propulsion issues, with identical confidence and lift values and a slightly lower conviction of 29.04. Rule 3 demonstrates that when Differential Global Navigation Satellite

System (DGNSS) is degraded, the main cause is a Position Reference System (PRS) failure, with a high confidence of 0.96, a lift of 5.68, and a conviction of 12.48, indicating a strong relationship. Rule 4 reveals that software failures as a secondary cause frequently lead to computer-related issues, with a confidence of 0.86, a lift of 6.12, and a conviction of 5.28. Environmental factors as the main cause (Rule 5) result in drift-off incidents with a confidence of 0.81, a lift of 1.9, and a conviction of 2.7. Rule 6 highlights that control system failures often lead to thruster/propulsion issues, with a confidence of 0.77, a lift of 2.8, and a conviction of 2.84. Rules 7 and 8 indicate that human factors, both as main and secondary causes, are significantly associated with drift-off incidents. The confidence levels are 0.76 and 0.74, respectively, with corresponding lift values of 1.78 and 1.74, and conviction values of 2.23 and 2.12.

Next, Tables 6 and 7 provide a detailed examination of specific failures and their immediate outcomes in DP incidents. These tables present the strongest confidence values associated with various consequences of DP incidents, such as LoP (drift-off, drive-off) and LoR. They also identify the types of root and secondary causes that serve as antecedents to these outcomes.

Rule	Antecedent	Consequent	Confidence	Lift
1	Root_Cause= Sudden changes/Current Sec_Cause= Human factor	Drift off	1.0	2.35
2	Root_Cause= Press standby button Sec_Cause= Human factor	Drift off	1.0	2.35
3	Root_Cause= Thruster trip Sec_Cause= Electrical failure	LoR	1.0	2.04
4	Root_Cause= Auxiliary System failure Sec_Cause= Auxiliary System failure	LoR	1.0	2.04
5	Root_Cause= OS failure Sec_Cause= OS failure	LoR	0.9	1.84
6	Root_Cause= Control system failure Sec_Cause= Electrical failure	LoR	0.9	1.83
7	Root_Cause= Pressing button by mistake Sec_Cause= Human factor	Drift off	0.8	1.88
8	Root_Cause= Feedback failure Sec_Cause= Electrical failure	LoR	0.8	1.63
9	Root_Cause= Thruster trip Sec_Cause= Thruster trip	LoR	0.77	1.58
10	Root_Cause= Control system failure Sec_Cause= Control system failure	LoR	0.71	1.45
11	Root_Cause= Lack of knowledge Sec_Cause= Human factor	Drift off	0.71	1.66
12	Root_Cause= Electrical failure Sec_Cause= Electrical failure	LoR	0.70	1.42

Table 6. Strong association rules (2) (Source: Authors)

Rule	Antecedent	Consequent	Confidence	Lift
1	Root_Cause= Incorrect command Main_Cause= Human factor	Drift off	1.0	2.35
2	Root_Cause= Press standby button Main_Cause= Human factor	Drift off	1.0	2.35
3	Root_Cause= Sudden changes/Current Sec_Cause= Human factor Main_Cause= Environment	Drift off	1.0	2.35
4	Sec_Cause= Human factor Main_Cause= Environment	Drift off	1.0	2.35
5	Root_Cause= Squalls Main_Cause= Environment	Drift off	1.0	2.35
6	Sec_Cause= Environment Main_Cause= Thruster/Propeller	Drift off	1.0	2.35
7	Root_Cause= Control system failure Sec_Cause= Control system failure Main_Cause= Power	LoR	1.0	2.04
8	Root_Cause= Thruster trip Sec_Cause= Electrical failure Main_Cause= Thruster/Propeller	LoR	1.0	2.04
9	Root_Cause= Auxiliary System failure Main_Cause= Thruster/Propeller	LoR	1.0	2.04
10	Root_Cause= Fuel system failure Sec_Cause= Fuel system failure Main_Cause= Power	LoR	1.0	2.04
11	Root_Cause= Mechanical failure Sec_Cause= Mechanical failure Main_Cause= Thruster/Propeller	LoR	1.0	2.04

Table 7. Strong association rules (3) (Source: Authors)

The findings provided in Table 7 indicate that human factors and environmental conditions play crucial roles and exert substantial influence on the loss of position in DP vessels, leading to drift-off incidents. Key human factors include incorrect commands (Rule 1) and pressing the stand-by button inappropriately (Rule 2). Environmental factors such as sudden changes in current (Rule 3) and abrupt squalls (Rule 5) also contribute significantly to serious DP incidents, causing vessels to lose their heading and position, subsequently drifting off. Rule 5 shows that in the event of unexpected squalls impacting the vessel's position, there is a significant likelihood of a drift-off incident. Therefore, maintaining continuous watchkeeping and monitoring meteorological conditions closely are crucial aspects of keeping DP watches. Additionally, it is recommended to incorporate meteorology training with DP operations, including procedures for responding to emergencies through diverse and severe weather conditions (squalls, solitons, currents, etc.), to ensure that all DPOs are adequately trained.

Table 8 highlights the strong association rules that link various root causes to specific incident outcomes, emphasizing the factors that lead to drift-off and LoR incidents. The data indicates that drift-off incidents are commonly attributed to human error antecedents, such as pressing the standby button or any button by mistake, the issuance of incorrect commands, and a lack of requisite knowledge. These human factors underscore the need for enhanced training and operational procedures to mitigate such risks.

Rule	Antecedent	Consequent	Confidence	Lift
1	Root_Cause= Squalls	Drift off	1.0	2.35
2	Root_Cause= Press standby button	Drift off	1.0	2.35
3	Root_Cause= Improper wiring	Drift off	1.0	2.35
4	Root_Cause= OS failure	LoR	0.92	1.87
5	Root_Cause= Swell/Wave	Drift off	0.92	2.16
6	Root_Cause= Thruster trip	LoR	0.82	1.68
7	Root_Cause= Sudden changes/Current	Drift off	0.80	1.88
8	Root_Cause= UPS failure	LoR	0.80	1.88
9	Root_Cause= Pressing button by mistake	Drift off	0.79	1.87
10	Root_Cause= Incorrect command	Drift off	0.77	1.81
11	Root_Cause= Hardware failure	LoR	0.72	1.47
12	Root_Cause= Control system failure	LoR	0.70	1.43

Table 8. Strong association rules (4) (Source: Authors)

Next, Table 9 provides a visual representation of the strong association rules related to operation types, vessel types, and consequent incidents. The data highlights the significant role of human and technical factors in different operational contexts, illustrating how specific root causes and secondary causes lead to particular incident outcomes.

Rule	Antecedent	Consequent	Confidence	Lift
1	Ops= Shuttle/FPSO Sec_Cause = Human factor	Drift off	1.0	2.35
2	Ops= Shuttle/FPSO Root_Cause= Pressing button by mistake	Drift off	1.0	2.35
3	Ops= Diving Sec_Cause= Blackout Main_Cause= Power	Drift off	1.0	2.35
4	Ops= Diving Root_Cause= OS failure	LoR	1.0	2.04
5	Ops= Cable/Pipe lay Sec_Cause= Human factor	Drift off	1.0	2.35
6	Ops= Drilling Sec_Cause= Electrical failure Main_Cause= Thruster/Propeller	LoR	1.0	2.04
7	Ops= Drilling Root_Cause= ThrusterTrip Main_Cause= Thruster/Propeller	LoR	1.0	2.04
8	Ops= PSV/Cargo Root_Cause= Control system failure Sec_Cause= Electrical failure	LoR	1.0	2.04
9	Ops= ROV Root_Cause= Control system failure Sec_Cause= Control system failure	LoR	1.0	2.04
10	Ops= ROV Sec_Cause= OS failure Main_Cause= Computer	LoR	1.0	2.04
11	Ops= PSV/Cargo Root_Cause= Hardware failure Main_Cause= Computer	LoR	1.0	2.04
12	Ops= PSV/Cargo Root_Cause= Thruster trip Sec_Cause= Thruster trip	LoR	1.0	2.04

Table 9. Strong association rules (5) (Source: Authors)

The Table 9 illustrates the correlation between various operational scenarios and the resultant DP incidents. Specifically, it shows that human factors and technical failures are critical antecedents in different ship operations. For instance, in Shuttle/Floating Production Storage and Offloading (FPSO) operations, human errors such as pressing the standby button by mistake consistently lead to drift-off incidents, as shown by a confidence value of 1.0 and a lift of 2.35.

In diving operations, blackouts and power-related issues are significant contributors to drift-off incidents, while Operating System (OS) failures predominantly result in LoR incidents. Cable/pipe lay operations also show a high incidence of drift-off incidents due to human factors.

For drilling operations, electrical failures and thruster trips are primary causes leading to LoR incidents. Similarly, in Platform Supply Vessel (PSV)/cargo operations, control system failures and thruster trips are significant antecedents for LoR incidents.

This analysis underscores the necessity for targeted preventive measures and enhanced training for personnel to mitigate human errors and technical failures, thereby improving the safety and reliability of DP operations across different vessel types and operational contexts.

3.1 Key Findings

3.1.1. Major Causes of DP Incidents

The analysis reveals that the major causes of DP incidents are as follows: thrusters and propulsion-related failures account for 24%, computer-related failures constitute 15%, power-related failures contribute to 14%, PRS failures represent 13%, and human factor-related failures comprise 9%.

3.1.2. Type of Operations during DP Incidents

The analysis of the type of operations during DP incidents shows that diving operations account for 17.3% of the incidents, drilling operations constitute 16.4%, ROV operations contribute to 14.6%, and cargo operations represent 12.5%.

3.1.3. Role of Human Factor

Human factors play a significant role in DP incidents, particularly in LoP incidents. In instances where human error is identified as the main cause, the consequence is an LoP incident in 87% of cases. Furthermore, if human error is identified as a secondary cause, the consequence results in an LoP incident in 88% of cases.

3.1.4. Consequences of Specific Failures

The consequences of specific failures were also analyzed. Power-related failures result in a 100% occurrence of LoP incidents. Similarly, thruster and propulsion failures lead to LoP incidents in 65% of cases.

3.1.5. Triggers of DP Incidents

Several triggers of DP incidents were identified. Pressing the wrong button or pressing a button by mistake triggers 55.2% of DP incidents. A lack of knowledge among DPOs contributes to 15% of incidents. DGNSS failures initiate 7.5% of DP incidents, while incorrect commands contribute to 6.6%, often related to personal experience and lack of knowledge.

3.1.6. DP Experience and Vessel Types

According to the author's previous research on the qualifications of DPOs (Sahin et al., 2023), the DP experience gained on supply vessels and drill ships differs significantly in terms of content and the amount of DP hours practiced. While the fundamentals of DP operations remain consistent, specific techniques and the nature of tasks vary considerably among different types of offshore vessels. Additionally, the DP classification is crucial; pipe lay and drill ships are predominantly classified as DP3, whereas other types of DP vessels generally fall under DP2 or DP1. Therefore, acquiring additional skills and experience may be necessary for DPOs.

3.1.7. Environmental Factors

Environmental factors consistently lead to drift-off incidents in all observed cases, resulting in a 100% occurrence rate. Conditions such as squalls, sudden changes in current, and swells/waves play a critical role in causing drift-off incidents, as evidenced by their high confidence values and lift. These findings suggest that environmental factors must be closely monitored and managed to prevent DP incidents.

3.1.8. Incident Outcomes by Operation Type

During drilling operations, 90% of DP incidents result in LoP incidents. Similarly, during diving operations, 82% of DP incidents result in LoP incidents. Cargo operations on PSVs account for 31.1% of all LoP incidents observed during DP operations.

3.1.9. Position Reference Systems

Using different sources for PRS does not guarantee the prevention of LoP incidents. In cases where the initial failure is attributed to PRS, the consequences include drift-off incidents in 85% of instances.

The results demonstrate that DP occurrences have a strong association with both human error and environmental factors. Particularly, there is a significant association between human factors (DPO fault) and LoP (drift off) incidents, as well as ship class/type (drill ships/operations). The accumulation of drift-off incidents occurred predominantly during major operations, including drilling (20%), ROV operations (13%), pipe lay-cable lay operations (13%), and diving operations (12.6%), collectively accounting for 58.6% of the total LoP (drift off) incidents during DP operations.

4. CONCLUSION

The objective of this study was to investigate the causes of DP incidents and identify potential preventive measures by analyzing DP incident data using an association rule learning approach. The results obtained from this analysis provide substantial evidence supporting the initial objectives.

The analysis revealed that the primary causes of DP incidents include thrusters and propulsion-related failures (24%), computer-related failures (15%), power-related failures (14%), PRS failures (13%), and human factor-related failures (9%). These findings align with the study's objective to identify key factors contributing to DP incidents.

Additionally, the data indicated that DP incidents predominantly occur during specific types of operations, such as diving (17.3%), drilling (16.4%), and ROV operations (14.6%). This insight addresses the objective of understanding the operational contexts in which DP incidents are most likely to occur, further highlighting the need for targeted preventive measures in these areas.

4.1. Recommendations

The study underscores the critical role of human factors, particularly in LoP (drift off) incidents, where human error as the main cause results in 87% of these LoP incidents. This evidence reveals the objective of examining the impact of human error on DP incidents and highlights the importance of enhancing DPO training and preparedness to prevent such incidents.

The association rules derived from the data revealed strong links between specific root causes and DP incident outcomes. For example, environmental factors, such as squalls and sudden changes in current, were shown to lead to drift-off incidents with high confidence. These findings validate the objective of identifying critical risk factors and developing strategies to mitigate their impact.

The data analysis presented in this paper highlights the significant impact of human error and technical failures on DP incidents. For instance, Table 7 and other association rule analyses demonstrate that many DP incidents can be traced back to inadequate knowledge and incorrect actions by DPOs. It is recommended that companies ensure that DPOs receive specific simulator training to enhance their ability to respond effectively during DP emergencies. This training should cover technical failures, adverse weather conditions, and their consequences, such as losing all wind sensors.

It is a well-recognized best practice in the maritime and offshore industries for personnel to familiarize themselves with all relevant documentation before commencing operations. However, this practice is not always consistently followed, leading to preventable DP incidents attributed to human factors and insufficient knowledge. Placing the responsibility on companies can ensure better adherence to this practice, promoting thorough preparation and continuous learning to prevent DP incidents. Prior to joining vessels, companies should ensure that DPOs review Failure Modes and Effects Analysis (FMEA), annual trial reports, the DP Manual, DP incident/failure reports (if available), the latest DP audit report, and other relevant documents. This recommendation is based on industry insights and empirical findings from the study, underscoring the critical role of comprehensive preparation in mitigating DP incidents.

In conclusion, this study achieved its objectives by identifying the main causes of DP incidents, understanding the operational contexts, and highlighting the importance of human factors. The findings provide a basis for recommending enhanced training and preparation for DPOs, which are crucial steps in improving the safety and reliability of offshore operations. Future research should focus on refining these association rules and further investigating the specific impacts of human error on DP incidents, and exploring advanced methodologies for more specialized analysis.

4.2. Suggestions for Future Study

Future research efforts should focus on refining association rules and investigating the specific impacts of human error on DP incidents. This deeper exploration could significantly enhance our understanding and contribute to the development of more effective strategies for preventing DP incidents.

Moreover, future studies could categorize different types of offshore vessels and DP equipment classes to individually analyze LoP incidents for each specific type of DP vessels. Employing advanced methodologies, such as machine learning or Bayesian network methods, can provide more sophisticated and precise insights into the causative factors and potential preventive measures for DP incidents across various operational contexts.

CONFLICT OF INTEREST

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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