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Accident data-driven human fatigue analysis in maritime transport using machine learning

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ABSTRACT

In maritime transport, fatigue conditions can impair seafarer performance, pose a high risk of maritime incidents, and affect safety at sea. However, investigating human fatigue and its impact on maritime safety is challenging due to limited objective measures and little interaction with other risk influential factors (RIFs). This study aims to develop a novel model enabling accident data-driven fatigue investigation and RIF analysis using machine learning. It makes new methodological contributions, such as 1) the development of a human fatigue investigation model to identify significant RIFs leading to human fatigue based on historical accident and incident data; 2) the combination of least absolute shrinkage and selection operator (LASSO) and bayesian network (BN) to formulate a new machine learning model to rationalise the investigation of human fatigue in maritime accidents and incidents; 3) provision of insightful implications to guide the survey of fatigue's contribution to maritime accidents and incidents without the support of psychological data. The results show the importance of RIFs and their interdependencies for human fatigue in maritime accidents. It takes advantage of available knowledge and machine learning to open a new direction for fatigue management, which will benefit the maritime fatigue investigation and provide insights into other high-risk sectors suffering from human fatigue (e.g. nuclear and offshore).

1. Introduction

With increasing automation of ships, human elements arguably play an increasingly crucial role in human-machine systems for maritime safety when the operators are moving from ships to shore control centres. 60.6 % of marine casualties and incidents were attributed to a human actions category; amongst accident event types for 2014–2020, 67.1 % of contributing factors are related to human action accident events [1]. For daily missions onboard, there is an increasing concern about psychological issues. For instance, more than half of pilots reveal the primary stressor is rough working time, and 79.8 % of them face high psychological demands in the workplace [2]. Due to high cognitive loads in the work environment for maritime operations, short-term and long-term psychological issues impact human perception and decision-making. Human fatigue is an issue for around-the-clock operations across various transportation modes and industries, particularly for the maritime sector [3]. In maritime transport, fatigue and burnout conditions can impair job performance, pose a high risk of maritime incidents, and affect safety performance [4,5]. Statistical analysis shows that 13.46 % of maritime accidents involving human errors are related to fatigue, which is associated with asleep and tiredness during navigation [6,7]. Owing to rough working time, sleep issues, shift length, and stress, fatigue assumes a greater significance in the near sea [8,9].

Fatigue is widely recognised as a significant factor in maritime accidents and plays a vital role in accident prevention. Specifically, fatigue means tiredness and physical discomfort due to prolonged activity [10, 11]. The most common elements contributing to fatigue in maritime transport are lack of sleep, inadequate rest, circadian rhythm (work/sleep at irregular times of the body clock), and pressure [3]. In addition, it comes up with jet lag, psychological and emotional factors, shift work, and workload [3]. Therefore, human fatigue has been a critical part of maritime transport and is closely connected with maritime operations and accidents. It has been considered in the International Maritime Organization (IMO) and the International Labour Organization (ILO) Conventions, which propose prescriptive working and rest hours as fatigue risk management requirements [12]. As compliance in international shipping, IMO regulations establish prescriptive rest intervals, requiring a minimum of 10 h of rest within a 24-h timeframe and 77 h

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over a 7-day span; the rest period can be split into a maximum of two segments with each lasting at least 6 h [13]. Addressing fatigue risk management through onboard technologies and resting period requirements is a significant part of safeguarding maritime safety [14].

Ship automation and job automation have grown significantly, especially for officers on board. However, job autonomy negatively impacts chronic fatigue [15,16]. To obtain maximum economic efficiency, shipping companies have increased automation to reduce the manning levels. However, some fatigue-related problems do not relieve but raise new risks in reduced manning levels that adversely affect crews in certain situations. For example, multiple tasks, such as cargo operations, accompanying surveyors and port state control (PSC) inspectors, should be conducted collectively when short turnarounds in ports. To complete such tasks, reduced manning power due to increased job autonomy leads to increased workload and inadequate teamwork support for individuals. In addition, it has addressed risks for them, such as a lack of sleep, fatigue, impaired performance, and diminished alertness. From this perspective, investigations on whether human fatigue exists in maritime accidents and incidents become crucial in ensuring safety at sea, particularly in the era of shipping autonomy. However, the relevant seafarer fatigue studies are still lacking and underdeveloped compared to other safety studies, because of their inherent technical difficulty in detecting real-time physiological response and quantified fatigue evidence. Therefore, any study on how objective factors such as visibility and accident type influence fatigue in maritime accidents could be ground-breaking and bring a paradigm shift in fatigue investigation and management.

Current fatigue investigation reveals a significant challenge: subjective measures are used to quantify human fatigue but expose inevitable bias without sufficient evidence; objective measures indicate the capacity to detect maritime operators' fatigue levels but show little connection with external related risk influential factors (RIFs). To compensate for the deficiency in subjective measures, this study initiates a new methodology by taking advantage of accident data and machine learning methods to open a new direction in human fatigue investigation from accidents. Meanwhile, interrelationships between critical fatigue-related RIFs are analysed using combined machine learning methods.

Specifically, this study aims to develop a novel model enabling accident data-driven fatigue investigation and RIF analysis using machine learning of historical accident records. The findings can guide fatigue management and accident prevention. In terms of its theoretical contributions, this study pioneers the combination of machine learning methods to optimise the BN-based accident analysis model with satisfied accuracy and improved robustness, which benefits data-driven risk assessment and complex network optimisation research. From an applied research perspective, this study takes advantage of accident data and machine learning approaches to open a new direction for fatigue management in the maritime industry first and the other risk-sensitive industries such as aviation later. It helps analyse how RIFs influence and predict the probability of human fatigue, contributing to fatigue investigation for accident prevention in practice.

The study shows the significance of RIFs for fatigue and its interrelationships with maritime accidents and incidents. The proposed novel methodology that can take advantage of previous knowledge and machine learning methods to identify critical fatigue-related factors and predict fatigue will open a new direction for fatigue management. It can help accident investigation organisations to investigate human fatigue's contribution to maritime accidents and incidents with minimum data and labour resources in maritime transport and other transport sectors, even providing insights into all accident prevention.

The structure of this paper is organised: Section 2 provides the literature review, followed by the proposed methodology for fatigue prediction in Section 3. In Section 4, the outcomes using data-driven modelling are presented. Next, the model validation is carried out to show the robustness and reliability of the proposed method. At last, Section 5 concludes the paper.

2. Literature review

2.1. Human fatigue in the maritime industry

In accordance with IMO's guidelines, fatigue can be characterised [3]:

> *"A state of physical and/or mental impairment resulting from factors such as inadequate sleep, extended wakefulness, work/rest requirements out of sync with circadian rhythms and physical, mental or emotional exertion that can impair alertness and the ability to safely operate a ship or perform safety-related duties."*

Referring to literature from the Web of Science with keywords "fatigue" and "maritime", there are 62 publications associated with human fatigue and relevant studies. Through a systematic review using CiteSpace software [17], human fatigue covers many topics and themes, such as "accident", "human factor", "human error", and "performance", as shown in Fig. 1. Its definitions and applications are closely connected with maritime operations [18]. Fatigue is classified into two main types: physical and mental fatigue. The former pertains to reduced performance in the muscular system, while mental fatigue is associated with reduced attention, diminished alertness, and a sense of weariness. The latter may be influenced by different work demands, which reveals chronic fatigue in seafarers. In addition, fatigue levels differ in various missions. Passenger and cargo ships' seafarers show higher fatigue levels than offshore workers [19]. The link between work attributes and chronic fatigue is investigated through a fatigue-related process, including inter-shift recovery, acute fatigue and sleep-related issues [15]. Objective physiological measurements using an armband monitor show seafarers' average sleep time is 5 h per day. Notably, nautical officers exhibit shorter sleep durations in comparison [20]. Therefore, it reveals significant associations between fatigue and sleep quality. With the increasing technologies on vessels, nautical officers undertake hectic workflows and are often exposed to insufficient rest times with reduced staff and unstable employment [21,22]. Compared to engine officers, deck officers may suffer an increasing workload from the documentation that affects rest hours [23]. In addition, automation in the maritime industry contributes to the increased number of duties but the reduced number of crew, leading to physical fatigue, while automated tasks excluding humans from the loop introduce passive involvements, leading to mental fatigue [21].

Fatigue shows less association with seafarers' age but is related to sleep quality issues, onboard noise levels, and night shifts [24–26]. In maritime operations, both deck and engine officers suffer from shift work with irregular sleep and rest. Typically, there are 2-watch systems with two watchkeepers sharing one day period, and 3-watch systems with three watchkeepers sharing. Van Leeuwen et al. [27] predict the on-watch severe sleepiness and the off-watch sleep, revealing the highest level of severe sleepiness for working 0000–1200 within 2-watch systems; the lowest sleepiness and most increased off-watch sleep for changeover (02–07–12–17–22) system within 3-watch systems. amongst three main roster types (6 h on/6 h off, 8 h on/8 h off and 4 h on/8 h off), the 4 h on/8 h off is with better sleep and minimised sleepiness [11]. Compared to 4 h on/8 h off watch systems, there is severe sleepiness amongst evening types at 04:00–06:00 h in the 6 h on/6 h off watch system [28]. Also, some studies show that sleep on watch usually occurs in the team working 00–04, particularly with free watch disturbance [29]. It is evident that sleepiness peaks in the early morning and night, which coincides with the fact that many maritime accidents occur. Eriksen et al. [30] find that sleepiness significantly increases at the end of watches during the 00:00–06:00 due to routine activity and boredom. Regarding officers of the watch, the (00:00–04:00, 12:00–16:00) and (04:00–08:00, 16:00–20:00) shifts impair cognitive functioning with sleepiness and impaired sleep quality during cargo handling operations [31].

To quantify seafarer's fatigue, subjective measurements have been

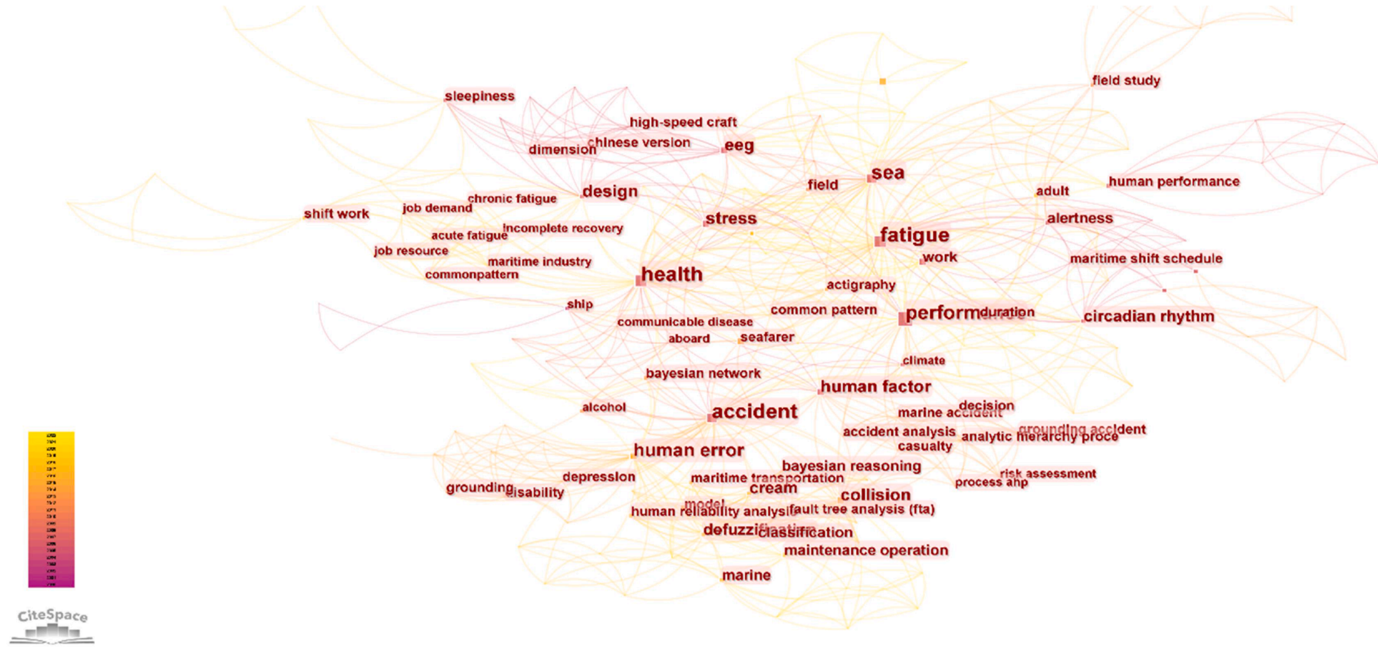

Fig. 1. Keywords of fatigue in the maritime sector (software: CiteSpace).

used to determine fatigue levels and mental symptoms onboard [8,32, 33,31]. The cross-sectional survey is designed to investigate sleepiness on duty [33], fatigue in maritime operations [15,34,31], and fatigue-related accident investigations [35]. In addition, questionnaires, such as the Piper Fatigue Scale (PFS), Symptom Checklist 90- Revised (SCL-90-R), Pittsburgh Sleep Quality Index (PSQI), Karolinska Sleepiness Scale (KSS), Psychomotor Vigilance Task (PVT), Arrow Flanker task performance, Skogby Excessive Daytime Sleepiness index (SEDS), Epworth sleepiness scale (ESS) score, actigraphy, and the Fatigue Avoidance Scheduling Tool (FAST) are used to study fatigue issues [36, 28,37,31].

In addition, objective measurements of human factors have been utilised in experimental studies [38–41] and real ships [24,42,26]. Some technologies have been utilised to investigate human fatigue. Specifically, the PsyCap as a psychological predictor is incorporated with the duration spent at sea to predict levels of fatigue and sleep quality amongst individuals onboard [19]. The non-invasive methods can be utilised to investigate cognitive tasks in many conditions with automated systems, which find that prefrontal cortex cooling after fatigue reduction effectively improves cognitive skills [43]. The wireless electroencephalogram (EEG) is used to detect the increase in mental fatigue levels of maritime operators through fatigue assessment algorithms [44, 41]. Moreover, the EEG is integrated with the electrocardiogram (ECG) for a simulated vessel piloting task to assess mental fatigue [45]. It shows the applicability of an algorithm with convolutional neural networks incorporated with Bayesian optimization, reaching 97.6 % test accuracy. The critical flicker frequency (CFF), changes in heart rate, blood pressure and saturation of peripheral oxygen can be indicators of cognitive fatigue [43]. In addition, wrist actigraphy can determine seafarers' sleep duration and wake time, which finds that fatigue levels are associated significantly with sleep quality rather than operation intensity [46].

The above studies prove the significance of human fatigue and its quantification in maritime operations. Subjective measurements of fatigue through surveys and questionnaires demonstrate a mature application, probably biased for evaluating fatigue levels. On the other hand, the objective measures using non-invasive technologies reveal a limited connection between fatigue and other related RIFs. Obviously, human fatigue studies from both subjective and objective perspectives are human-focused and fail to take into account the impact of other RIFs. It is evident that there is no study in the current literature to use accident data to quantify the relationships between human fatigue and related RIFs, so as to reveal the comprehension of fatigue contributing to accidents. One of the novelties of this study is the incorporation of objective RIFs into a fatigue-related data-driven model to reveal their contributors to maritime accidents and incidents.

2.2. Risk factors for human fatigue investigation

It is critical to conduct a risk analysis of human fatigue in accident investigations because it can adversely affect seafarers' performance [47]. The risk of ship accidents increases when seafarers are fatigued, especially for collisions and groundings [35,48,49]. Collision accidents with fatigue issues are characterised by wrong-timed decisions, mistakes, and poor communication; fatigue-related groundings are related to overlooking and asleep [50]. Fatigue also contributes to unsafe behaviours, such as over-reliance on technology in navigation [51]. Therefore, it is significant to investigate human fatigue and related RIFs in the maritime sector.

Human fatigue is mainly investigated through shift work and sleep. Crews who conduct shift work in such watch systems demonstrate a high level of fatigue [11,52]. Specifically, the feeling of fatigue can be explained by disruptions in sleep patterns and circadian rhythms [53]. amongst them, circadian rhythms pertain to changes in physiological or psychological functioning that occur based on the time of day [10]. It has been found that maritime pilotage involving on-call work styles may result in sleep shortage and circadian misalignment [54]. To investigate sleep quality, sleep-wake behaviours, such as time and length, and self-reported methods are utilised to study fatigue's impacts on roster status and "on-call" status [55]. It reveals that long and irregular working hours compromise human performance and safety in maritime pilotage [29]. Besides, alcohol intake and consumption of caffeinated drinks are significant causes of human fatigue and sleep [56,57]. The managers' interventions for safety compliance contribute to increased workloads, psychological pressure and fatigue [58].

The long working hours and related work situations introduce high risks of being in fatigue conditions. Regulations have addressed adequate hours of rest but have not addressed the challenges and practice of dynamic working schedules and human psychophysiology [16]. The impact of long-term and high cognitive loads on human fatigue is a psychological problem that impacts seafarers' health [59]. Although advanced technologies and ship automation have reduced the number of crews, it has introduced increased workload for officers onboard [15,16]. Given multiple duties and responsibilities, especially for officers of the watch, reduced manning levels and increased workload do not guarantee adequate rest. The chief officers' working hours are positively related to the number of ports of call, but negatively associated with the transit distance at short sea shipping [60]. From a practical perspective, the ship type reveals different impacts on the work intensity. For instance, the work intensity of deck officers in tanker and container ships during short-sea navigation is higher than in other ship types [22]. Different cargo types require different procedures under rules for specific ship types (i.e., tankers), showing various work intensity levels. In addition, short-sea seafarers engaging in intricate tasks experience a higher level of work intensity compared to their international counterparts, where vessel docking and disembarking are more frequently and often navigating restricted channels. The former experiences prolonged working hours and interrupted rest time [23]. However, fatigue does not show linear correlations with increased work intensity but reveals a significant association with sleep [35,46]. In addition, safety climate contributes to human fatigue [50] and can predict the following week's sleep quality and fatigue amongst seafarers [35].

In addition, various methodologies have been utilised to analyse fatigue in maritime sector. Akhtar and Utne [50] study fatigue using the Cognitive Reliability and Error Analysis Method (CREAM) model. Common fatigue factors include "inattention", "shift work", "inadequate procedures", "irregular working hours", "observation missed", "inadequate task allocation", "excessive demands", and "communication failure" [50]. However, it can not reflect the relationship between these RIFs. Gander et al. [42] develop fatigue management strategies by comparing sleep and sleepiness of deckhands at home and at sea using the Karolinska Sleepiness Scale (KSS). The Bayesian network (BN) has been incorporated with a modified Human Factor Analysis and Classification System (HFACS) to analyse the effect of fatigue on groundings, showing that a fatigued operator contributes to 23 % higher grounding probability in long transit [61]. The BN is also applied to predict human errors and shows a high level of fatigue and stress in the engine and nautical officers [62]. Although some RIFs contributing to fatigue are identified through accident reports, scarce studies focus on how human fatigue associated with RIFs results in maritime accidents and incidents.

Currently, the studies on human fatigue-related RIFs are at large presented in a piecemeal form, hence lacking a systematic methodology for a complex model with a great number of variables. In addition, classical models for fatigue investigation have such limitations as factor selection and data requirements. For instance, psychophysiological data for seafarers' sleep patterns are often not accessible during fatigue investigation. To fulfil this gap, this study incorporates the Least Absolute Shrinkage and Selection Operator (LASSO) and BN to shrink critical RIFs and predict human fatigue in maritime transport using accident data. Consequently, it provides new insights into fatigue investigation with limited psychophysiological data and benefit fatigue management for maritime authorities.

2.3. New contributions

This study incorporates LASSO and BN to analyse fatigue and the associated RIFs through accident data-driven investigation. Specifically, its novelties and contributions include:

- Utilisation of historical records to generate a human fatigue model to identify significant factors from an objective accident/incident occurrence perspective.
- Combination of LASSO and BN to propose a data-driven model to investigate human fatigue.
- Providing a guideline to research fatigue's contribution to a maritime accident or incident without sufficient psychological data.

The study shows the significance of RIFs for fatigue and its interrelationships with maritime accidents and incidents. The proposed novel methodology that can take advantage of previous knowledge and machine learning methods to identify critical fatigue-related factors and predict fatigue will open a new direction for fatigue management. It can help investigation organisations to investigate human fatigue's contribution to maritime accidents and incidents with minimum data and labour resources in maritime transport and other transport sectors, even providing insights into all accident prevention.

3. Methodology

3.1. Data collection

Raw historical data is collected from the transportation safety board of Canada (TSB) from 1995 to 2022 (March) to identify fatigue-related RIFs. Out of 82,909 records, there are 310 pieces of accident/incident data with fatigue investigation by the TSB. After removing duplicated records and deleting the data without fatigue investigation results, 104 maritime accidents and incidents with fatigue investigation remain. To investigate human fatigue in maritime accidents/incidents, details of each RIF defined by the TSB and used in each investigation report are presented in Table 1. The investigated variable is "FatigueContFactorEnum" which means whether fatigue was a contributing factor ("Yes"), or not ("No") in the occurrence.

3.2. A new human fatigue analysis model by combined least absolute shrinkage and selection operator (LASSO) and bayesian network (BN)

Currently, numerical analysis and modelling of fatigue-related risk analysis are rare due to historical accident/incident data constraints. Few studies utilise machine learning methods to facilitate data analysis and risk prediction of human fatigue. A BN is a probabilistic graphical model to investigate causal relationships between different nodes and explore the probability for the target node given specific findings, which has been utilised in maritime safety and security [63,64]. This method takes advantage of the fusion of multiple data sources, such as empirical

Table 1
Risk factors and their descriptions (Source: the TSB).

Factor	Description
OccClassID	Classification of the occurrence by the TSB
TimeZoneID	The time zone of the occurrence time
ProvinceID	The province of the occurrence location
OccurrenceTypeID	Whether the occurrence was an accident or reportable incident
AccIncTypeID	Accident/incident type
IMOClassLevelID	International Maritime Organization class level
InjuriesIND	Injuries
SearchAndRescueIND	Search and rescue
DamageIND	Damage
PollutionIND	Pollution
AreaTypeID	Area type
RoutingID	Routing
WithInPilotBoardingAreaEnum	Within pilot boarding area
WeatherFactorEnum	Weather factor (yes or no)
RegionOfOccurrenceID	Region of occurrence
RegionResponsibilityID	Region of responsibility
VisibilityDistance_Nm	Visibility distance (nautical miles)
LightConditionID	Light condition
WeatherConditionID	Weather condition (e.g. clear, fog, overcast, rain)
WindSpeedTypeID	Wind speed type
WindSpeed_Knots	Wind speed (knots)
SeaStateID	Sea state (e.g. calm, smooth, slight, moderate, rough)
ReportedByID	Reported by whom

data and expert judgments, to tackle the analysis of safety-critical systems under high uncertainty due to limited historical records. For instance, it is incorporated with HFACS to investigate human fatigue factors, showing 23 % higher probability of grounding [61]. Asadayoobi et al. [65] modify a BN with a new dimension to update performance leading factors and predict human reliability. In addition, BN can demonstrate the dependencies amongst variables, revealing a wide range of applications in data-driven models [66,67]. It can be utilised in three types of human reliability analysis methods (rule-based, data-based, and semi-rule-based methods) to calculate human error probabilities [68]. Quantitative causation analysis in Arctic waters shows critical factors in grounding accidents are poor traffic conditions, poor situational awareness, and inefficient use of navigation equipment [69]. However, its limitation on calculating conditional probability tables (CPT) affects BN's accuracy in a complex network with enormous nodes. In addition, a large number of nodes with moderate or small data deteriorate the performance of sensitivity analysis and model validation [6,70]. Due to the large number of nodes and moderate size of data for the fatigue-related study, it is not appropriate to generate a data-driven BN model with all nodes directly due to the well-recognised challenge in the configuration of CPTs. Therefore, it is of huge methodological value to develop a new method to shape and optimise the BN structure with reduced nodes.

To compensate for this deficiency in the BN, a novel methodology for fatigue risk analysis combing machine learning methods is proposed. The LASSO, as a machine learning approach, is a regression analysis method that selects variables and performs regularisation by minimizing the residual error subject to the constraint [71]. This algorithm for shrinking unnecessary variables has been used to calculate fuel consumption of a container ship [72,73] and monitor ship operational performance [74]. It takes advantage of the way of penalty using an absolute value as regularisation parameter, resulting in smaller models with fewer predictors. In this way, fatigue-related RIFs in the BN model can be reduced using the LASSO method.

This study incorporates the LASSO into BN modelling to optimise the BN structure by striking a good balance between the reduced RIFs and satisfactory accuracy of results. Firstly, it conducts the cross-validation error using LASSO for each parameter value and then selects the one for which the error is minimised. Specifically, LASSO solves the optimal problem by

$$\min_{\beta_0,\beta}\left(\frac{1}{2S}\sum_{i=1}^{S}\left(y_i-\beta_0-x_i^T\beta\right)^2+\lambda\sum_{j=0}^{p}\left|\beta_j\right|\right) \tag{1}$$

Where S is the number of accident/incident records, p is the number of RIFs, y_i is the response variable at record i, x_i represents the vector of p values at record i, λ is a positive tuning parameter, the parameters β_0 and β are scalar and p-vector. The λ controls the strength of the L1 penalty. When $\lambda = 0$, no RIFs are eliminated. As λ increases, the model bias increases with more RIFs being removed.

To select an appropriate λ to remove irrelevant RIFs, this study conducts cross-validated fits. The remaining RIFs serve as the input of BN model in the next step. Such selection of factors will help reduce the number of nodes in a data-driven BN model, simplifying the CPT calculation and data requirements for the BN model without compromising the prediction accuracy too much.

Then, this study utilises the BN method for human fatigue modelling, which defines a joint probability distribution encompassing random variables $U = \{A_1, \ldots A_n, C\}$, where n is the count of identified RIFs, and $A_1, \ldots A_n$ denote RIFs, while C stands for "FatigueContFactorEnum". The formulation of the joint probability distribution is as follows:

$$P(A_1, \ldots A_n, C) = P(C)\cdot\prod_{i=1}^{n}P(A_i|C) \tag{2}$$

A data-driven approach is utilised for BN modelling without expert knowledge to predict the likelihood of fatigue in maritime accidents and incidents. To unveil the interdependencies amongst objective RIFs for "FatigueContFactorEnum", a BN model is generated using accident data, as well as the calculated CPTs in the BN. Such a data-driven risk assessment model is built in two steps: 1) generate the BN structure between various nodes by using a tree-augmented naive Bayes (TAN) learning algorithm [6,70,75]; 2) calculate the CPTs based on the historical data. TAN learning finds an optimised tree structure defining the function over risk factors using conditional mutual information [76,6]. The maximised conditional mutual information can be calculated as

$$I_P\left(A_i, A_j|C\right) = \sum_{a_{ii},a_{ji},c_i}P\left(a_{ii}, a_{ji}, c_i\right)\log\frac{P\left(a_{ii}, a_{ji}|c_i\right)}{P\left(a_{ii}|c_i\right)P\left(a_{ji}|c_i\right)} \tag{3}$$

where a_{ii} is the i^{th} state of risk factor A_i, a_{ji} is the i^{th} state of risk factor A_j, c_i is the i^{th} state of "FatigueContFactorEnum", I_P represents the conditional mutual information. The detailed steps for configuring a tree structure using TAN are found in Appendix A (e.g. Yang et al. [77] and Fan et al. [6]).

3.3. Fatigue analysis model validation

The mutual information, as a standard sensitivity analysis method, represents dependencies between two nodes in the probabilistic theory and can give the information shared with "FatigueContFactorEnum" [77]. This study uses mutual information to investigate the connections amongst selected RIFs and the fatigue investigation result.

Subsequently, scenario simulation is used to explore the consequences of various RIFs. This study calculates the impact of the multi-state variables against fatigue results (i.e. Yes or No) [78]. Particularly, it determines the High-Risk Influence (HRI) of a risk factor to the "Yes" state of "FatigueContFactorEnum" by elevating the probability of the state with the greatest impact on the "Yes" outcome to 100 %. Following this, the Low-Risk Inference (LRI) is calculated by raising the probability of the state with the least impact on the "Yes" outcome to 100 %. This sequence is then replicated for the "No" outcome. Therefore, the HRI and LRI values of all RIFs are obtained.

Moreover, minor variable changes are conducted through scenario simulation to satisfy the axiom for sensitivity analysis, proposed by Yang et al. [79]. Specifically, the state with HRI (first factor) to the state "Yes" of "FatigueContFactorEnum" increases by 10 %, while the state with LRI to "Yes" decreases by 10 % [6]. Then, the same procedure is applied to another risk factor until all updated values are obtained. The values on the state "Yes" of "FatigueContFactorEnum" should gradually increase to satisfy the mentioned axiom. Subsequently, the same procedures are applied to the state "No" of "FatigueContFactorEnum". Similarly, the updated values should gradually increase along with involving more RIFs to meet the axiom.

The BN model can also be validated by simulating previous maritime accident/incident cases [70,77]. Given the observed states of several RIFs, how "FatigueContFactorEnum" is revealed implies whether there is consistency between the model and reality.

4. Results and discussions

4.1. Risk factor selection

The study constructs the lasso fit employing a 6-fold cross-validation approach, which finds the highest Lambda value when the mean squared error (MSE) falls within the standard error range of the minimum cross-validated MSE. As shown in Fig. 2, the green circle represents an index of 94, where the Lambda is with minimum cross-validation error. Therefore, it removes unnecessary RIFs and remains critical RIFs as predictor variables in the model, i.e. "LightConditionID", "AccIncTypeID", "AreaTypeID", "VisibilityDistance_Nm", "DamageIND". The description of each factor is listed in Table 2 regarding the TSB accident/incident

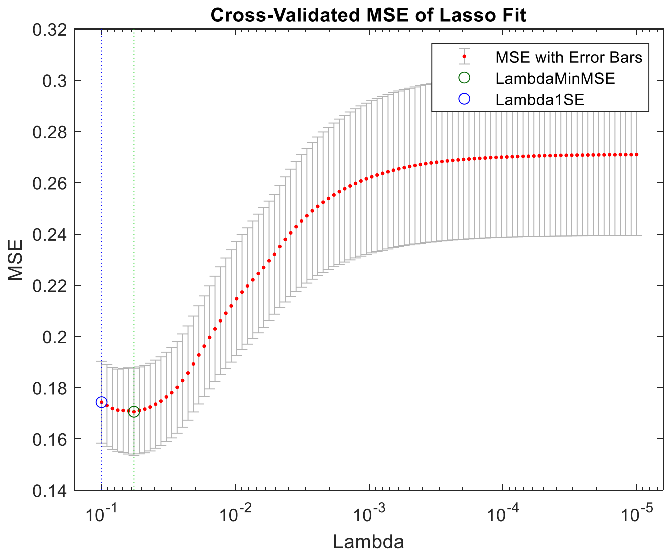

Fig. 2. LASSO fit model.

Table 2
States for the selected RIFs.

Factor	States
LightConditionID	1 (day), 2 (night), 3 (twilight), 4 (unknown)
AccIncTypeID	1 (grounding), 2 (collision), 3 (total failure of machinery or technical system), 4 (person seriously injured or killed - boarding, being on board, falling overboard from the ship), 5 (sank), 6 (others)
AreaTypeID	1 (at sea), 2 (channel/strait/sound), 3 (harbour area), 4 (river), 5(others)
VisibilityDistance_Nm	1 [0–10) nm, 2 [10–20] nm, 3 >20 nm, 4 (unknown)
DamageIND	61 (yes), 62 (no), 63 (unknown), 64 (none apparent)

reports. amongst them, the visibility distance represents the distance visible to eyes with the possible help of onboard equipment such as binoculars.

4.2. Data-driven modelling

To predict fatigue investigation (whether human fatigue contributes to an accident or incident), this study generates a new model integrating LASSO and BN approaches. After selecting the critical RIFs using LASSO, the BN model is built through a data-driven methodology. The variable “FatigueContFactorEnum” has “Yes” and “No” states as the target node.

To generate the BN structure in the first step, a TAN learning algorithm is utilised to find the optimised structure of BN with maximum conditional mutual information. In the second step, the CPTs are calculated based on historical data. Following such steps, the BN model is illustrated in Fig. 3.

In the above BN model, the fatigue investigation result (“FatigueContFactorEnum”) is considered as the parent node. At the same time, critical RIFs (“LightConditionID”, “AccIncTypeID”, “AreaTypeID”, “VisibilityDistance_Nm”, “DamageIND”) are child nodes. The proposed model reflects the relationships between critical RIFs and human fatigue, as well as the interdependencies amongst different nodes. Given the moderate size of the data, the BN model with a large number of nodes makes fatigue prediction insensitive. Therefore, the proposed model with fatigue-related RIFs will improve the performance of the BN given such a situation. It can help analyse RIFs’ influence and predict the probability of human fatigue (whether human fatigue is a contributing factor to accidents or incidents), which provides a rational answer to fatigue’s contributory before any fatigue investigation (e.g., sleep or rest schedule) conducted [80].

4.3. Model validation

To reflect interdependencies amongst RIFs, the mutual information is calculated to investigate the sensitivity of the node “FatigueContFactorEnum” in the BN, as shown in Table 3. Regarding the mutual information between each risk factor and fatigue, the above table shows that the rank of influence of RIFs on fatigue is: Region of occurrence >

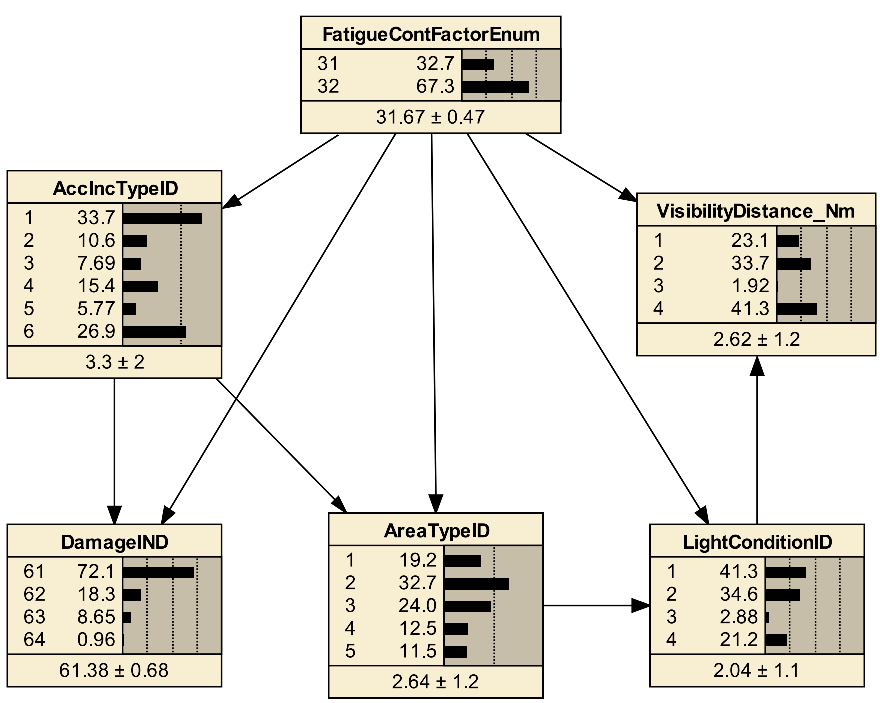

Fig. 3. Human fatigue model using the TAN approach.

Table 3
Sensitivity of “FatigueContfactorEnum” in response to a finding at a different node.

Node	Mutual information
LightConditionID	0.16689
AccIncTypeID	0.11825
AreaTypeID	0.07262
VisibilityDistance_Nm	0.05581
DamageIND	0.03646

Reported by whom > Pollution > Accident/incident type > Within pilot boarding area > Light condition.

Regarding the scenario simulation in Section 3.3, another sensitivity analysis is conducted to investigate the influential level of different states of different nodes on fatigue, as shown in Table 4. In addition, HRIs and LRIs values are obtained through this procedure.

From Table 4, each critical risk factor’s effect on human fatigue is given individually. Specifically, the “3” state of “LightConditionID” node shows the highest probability of the “Yes” state of fatigue, which means that there is the highest likelihood of fatigue contributing to maritime accidents and incidents in twilight conditions. On the contrary, the “1” state of “LightConditionID” node reveals the lowest probability of the “Yes” state of fatigue, which means that there is the lowest probability of fatigue contributing to maritime accidents and incidents in the day. In addition, the “1” state of “AccIncTypeID” node shows the highest probability of the “Yes” state of fatigue, which means that grounding has the highest likelihood of being involved in accidents/incidents with fatigue as a contributing factor. On the contrary, the “4” state of “AccIncTypeID” node reveals the lowest probability of the “Yes” state of fatigue, which means that person seriously injured or killed has the lowest probability of fatigue in maritime accidents/incidents. A similar analysis can be explained in other nodes. Because the state of investigated node “FatigueContFactorEnum” only has two states, indicating “Yes” and “No”, node states of HRI and LRI in the “31” column are consistent with those in the “32” column.

In addition, minor changes in variables are incorporated within the scenario simulation, as shown in Table 5. The updated value on the state “Yes” of “FatigueContFactorEnum” is gradually increasing along with the subsequent increase of each node. Also, the same increasing trend can be found in the updated values of state “No”. The results show multiple factors influence the states of the investigated node “FatigueContFactorEnum”. Therefore, it satisfies the assumed axiom and proves the robustness and reliability of the proposed BN model.

Table 4
Scenario simulation to calculate HRIs and LRIs.

Risk factor		fatiguecontfactorenum	
Node	State	Yes	No
lightconditionid	1	9.3(LRI)	90.7(HRI)
	2	38.9	61.1
	3	66.7(HRI)	33.3(LRI)
	4	63.6	36.4
Accinc typeid	1	54.3(HRI)	45.7(LRI)
	2	45.5	54.5
	3	25.0	75.0
	4	6.25(LRI)	93.75(HRI)
	5	16.7	83.3
	6	21.4	78.6
Area typeid	1	30.0	70.0
	2	52.9(HRI)	47.1(LRI)
	3	24.0	76.0
	4	15.4(LRI)	84.6(HRI)
	5	16.7	83.3
Visibility distance_Nm	1	29.2	70.8
	2	20.0	80.0
	3	<0.1(LRI)	>99.9(HRI)
	4	46.5(HRI)	53.5(LRI)
Light conditionID	61	38.7(HRI)	61.3(LRI)
	62	15.8	84.2
	63	22.2	77.8
	64	<0.1(LRI)	>99.9(HRI)

Table 5
Minor changes of nodes within scenario simulation.

Light conditionID	/	**10 %**	**10 %**	**10 %**	**10 %**	**10 %**
AccInctypeID	/	/	**10 %**	**10 %**	**10 %**	**10 %**
AreatypeID	/	/	/	**10 %**	**10 %**	**10 %**
Visibilitydistance_Nm	/	/	/	/	**10 %**	**10 %**
DamageIND	/	/	/	/	/	**10 %**
FatiguecontFactorEnum Yes (31)	32.7	35.0	36.4	37.9	38.4	38.9
Fatigue contFactorEnum No (32)	67.3	69.5	70.8	71.8	72.5	75.5

In theory, multiple test case datasets reveal more evidence to support the model validation. However, in reality, when the overall datasets are small, the use of a few selected real cases to test the model’s reliability and robustness is widely accepted in the literature [6,70,77]. At last, case study validation is conducted with a real incident case which was not included in the database and happened more recently. Specifically, it was a passenger vessel, “KAWARTHA SPIRIT”, running aground in Purcells Cove and then returned under its own power in October 2022. The details of the historical data are given in Fig. 4: accident type was bottom contact (AccIncTypeID state “6”); had vessel damage (DamageIND state “61”); took place in the area of bay (AreaTypeID state “5”); visibility distance was 0.4 nm (VisibilityDistance_Nm state “1”); light condition was in day (LightConditionID state “1”). After assigning each state of the node, it can be seen from the BN network that the parent node FatigueContFactorEnum presents its updating state: the probability of fatigue as a contributing factor is around 0 (state “31”), which is consistent with the actual fatigue investigation result given by the investigation organisation: fatigue, was not a contributing factor, involved in this bottom contact incident.

5. Implications and discussions

The proposed machine learning methodology has made two insightful contributions: an enabler of accident data-driven fatigue investigation and the associated risk factor analysis in practice and a solution for data-driven BN training with a small number of data using LASSO in theory. Firstly, the LASSO removed irrelevant RIFs associated with fatigue in maritime accidents and incidents. Then, the LASSO outputs the critical related factors, i.e. light condition, accident or incident type, area type, visibility distance, and vessel damage. Moreover, the BN is constructed to show the importance of different risk influential factors for fatigue and its interdependencies in maritime accidents and incidents. It will no doubt significantly benefit the stakeholders, including shipping companies, maritime administration/authorities and researchers in both maritime safety and human reliability areas for better safety at sea and even beyond across other sectors involving high-level human fatigue effect on operation safety (e.g. nuclear and air transportation).

With regard to theoretical implications, this study proposes a novel methodology combining LASSO and BN, reducing nodes and simplifying network complexity. Specifically, the LASSO is utilised to select critical RIFs as nodes, which appropriately shapes the BN structure with reduced nodes. Furthermore, it incorporates machine learning methods, i.e., the LASSO and the BN, to optimise the model with satisfied accuracy and improve the robustness of the probability model. Therefore, it can be of high generality and benefit data-driven risk assessment methodology and complex network optimisation. This success could significantly stimulate the BN’s applications in safety science in general and maritime risk analysis in specific.

Regarding practical implications, this study takes advantage of accident data and machine learning approaches to open a new direction

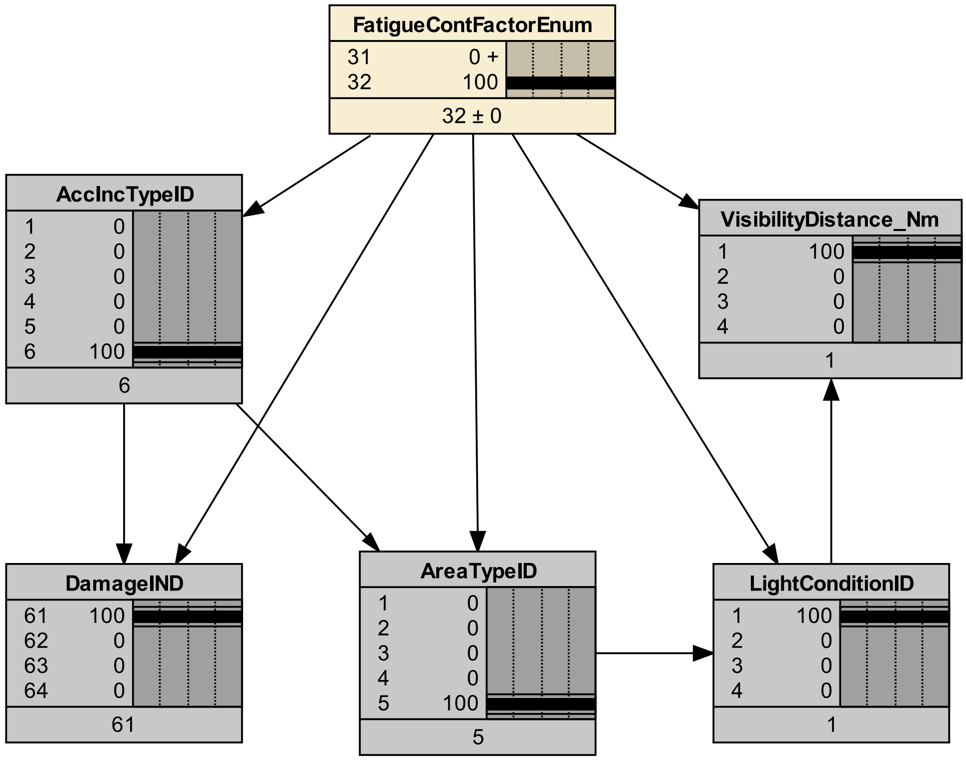

Fig. 4. Case study of a passenger vessel incident.

for fatigue management. Case study results in section 4.3 can help analyse how RIFs influence and predict the probability of human fatigue (whether human fatigue contributes to accidents or incidents). Compared to the literature utilising physiological signals to investigate mental workload and fatigue [81], this work reveals a connection between fatigue and other related RIFs, overcoming the drawbacks of artefact vulnerability and prolonged device wearing time for physiological measurements. The results evidently complement the objective evaluation of mental fatigue in terms of accident data-driven analysis. Typically, fatigue investigation needs to find fatigue existence by checking factors such as acute sleep disruption, chronic sleep disruption, prolonged wakefulness, the impact of circadian rhythms, sleep disorders, and relevant medical and psychological conditions [80]. Then, an investigation of fatigue's impact is conducted by observing performance impairment associated with decision-making, information processing, attention, reaction time, and mood. This model can recommend maritime authorities perform a detailed fatigue investigation on the accident with a high probability of fatigue contribution. Regarding the accident with a low likelihood of fatigue, it may refer to a third agency or other resources to decide whether to take subsequent measures on fatigue investigation. Moreover, the updated probability of the investigated fatigue node can be tested by adjusting different nodes. The adjustments that reduce the likelihood of fatigue can be used to manage and prevent fatigue in maritime transport. This study provides maritime authorities and organisations with a rational cue on fatigue contributions before fatigue investigation, which will benefit fatigue investigation in maritime transport and other transport sectors and even offer insights into all accident prevention.

6. Conclusions

This study aims to develop a novel method integrating machine learning methods enabling accident data-driven fatigue investigation and the associated risk factor analysis. It utilises historical data to investigate how fatigue-related RIFs interact and influence maritime accidents and incidents. It incorporates the LASSO and the BN to select critical RIFs and optimise a quantitative model. The results show significant RIFs in fatigue investigation and its interrelationships in maritime accidents, i.e. light condition, accident type, area type, visibility distance, and vessel damage. Its contributions include: 1) generating a human fatigue model to identify significant factors for human fatigue-contributing accidents; 2) incorporating LASSO and BN methods to propose a novel data-driven methodology to investigate relationships between RIFs and human fatigue; 3) prediction of human fatigue through a rational selection of RIFs, providing a supportive tool for fatigue investigation with insufficient data.

The proposed methodology of fatigue investigation provides new insights for maritime accident investigation. Even referring to the data reported by various sectors, it is hard to generate a fatigue prediction model when too many factors are involved. Data with a small sample size (maritime accidents and incidents with fatigue issues) but enormous nodes (RIFs) complicate the BN model with large CPTs that cannot be appropriately calculated. Therefore, the developed methodology reduces the number of nodes in the BN by conducting the LASSO model, which benefits a rational selection of critical RIFs of fatigue. On the other hand, before fatigue investigation, there is usually limited fatigue-related data obtained from public resources. Without sufficient fatigue-related information, such as sleep time, sleep quality, and rest schedules, it is difficult to judge whether fatigue contributes to maritime accidents and incidents [80]. However, by utilising the modified BN model, maritime authorities and investigation organisations can observe whether fatigue contributes to accidents and incidents with objective occurrence findings in the case study of this work. The proposed model can be used as a universal one applicable to any established maritime accident database. The philosophy lies in modifying the original BN model to enable complex network analysis with moderate data size. The TSB data is chosen as it is representative and has been widely used in maritime accident analysis [82,83]. When and if the new methodology is applied to other databases or even those from other sectors (e.g. nuclear and aviation), the parameters and model structure representing the numerical connections of data will change. Therefore, it can serve as a tool to take advantage of available knowledge and machine learning for fatigue management at sea and even beyond across other sectors involving high-level human fatigue effects on operation safety. However, this work has a limitation in terms of not fully accommodating vessel factors in fatigue-related accidents and incidents. In future work, the proposed data-driven network will complement more RIFs including vessel and voyage features, when and if the relevant data becomes available.

CRediT authorship contribution statement

Shiqi Fan: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Zaili Yang:** Writing – review & editing, Supervision, Project administration, Funding acquisition.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

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Data availability

Data will be made available on request.

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Appendix A. Construction of a TAN trained BN model in the context of human fatigue analysis

Let $A_1, \ldots, A_n$ denote the fatigue-related RIFs and C represent the fatigue investigation result "FatigueContFactorEnum". Π_C is the parent variables of C. B denotes a TAN model if $\Pi_C = \emptyset$, and there is a function π that defines a tree over fatigue-related RIFs such that $\Pi_{A_i} = \{C, A_{\pi(i)}\}$ if $\pi(i) > 0$, and $\Pi_{A_i} = \{C\}$ if $\pi(i) = 0$. The purpose is to identify a tree-defining function π over fatigue-related RIFs such that the log likelihood is maximised. The result is adopted as the structure for the BN model. However, due to the Bayesian inference applied to the outcomes, it is permissible for links to flow in either direction in order to better align with real-world observations. Stated differently, the orientations of connections within the TAN model can be suitably modified to align with specific requirements, which is widely accepted in BN modelling and reasoning.

The procedure of constructing TAN offers a solution to the optimisation problem. This method uses conditional mutual information between fatigue-related RIFs given the "FatigueContFactorEnum". This function is defined as

$$I_P(A_i; A_j|C) = \sum_{a_{ii}, a_{ji}, c_i} P(a_{ii}, a_{ji}, c_i) log \frac{P(a_{ii}, a_{ji}|c_i)}{P(a_{ii}|c_i)P(a_{ji}|c_i)}$$

where I_P represents the conditional mutual information, a_{ii} is the ith state of the RIFs A_i, a_{ji} is the ith state of the RIFs A_j, c_i is the ith state of the class variable C_i. This function measures the information both RIFs provide when the value of C is known.

The procedure of constructing TAN for this study involves six main steps:

a) Compute $I_P(A_i, A_j| C)$ for each pair of RIFs, $i \neq j$.
b) Establish a complete undirected graph in which the nodes represent RIFs $A_1, \ldots, A_n$. The weight of an edge connecting A_i to A_j is $I_P(A_i, A_j| C)$.
c) Construct a maximum weighted spanning tree. The maximum weighted spanning tree is the tree that possesses a maximum sum of $I_P(A_i, A_j| C)$.
d) Convert the undirected tree into a directed one by choosing a root variable and orienting all edges outward from it.
e) Formulate a TAN model by introducing a vertex labelled by the "FatigueContFactorEnum" and adding an arc from the vertex to each RIF A_i.
f) Calculate the conditional probability of each fatigue-related RIFs.

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