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Dynamic logistics disruption risk model for offshore supply vessel operations in Arctic waters

Sidum Adumene [a,*], Modestus Okwu [b], Mohammad Yazdi [a], Mawuli Afenyo [c], Rabiul Islam [d,*], Charles Ugochukwu Orji [e], Francis Obeng [f], Floris Goerlandt [g]

[a] Faculty of Engineering and Applied Science, Memorial University of Newfoundland, St. John's NL, Canada A1B 3 × 5
[b] Department of Mechanical and Industrial Engineering, University of Johannesburg, Johannesburg, South Africa
[c] Texas A & M University, 200 Seawolf Pkwy, Galveston, TX 77554, USA
[d] National Centre for Ports and Shipping (NCPS), Australian Maritime College (AMC), University of Tasmania, Launceston, Tasmania 7250, Australia
[e] Centre of Excellence in Marine and Offshore Engineering, Rivers State University, Port Harcourt, Nigeria
[f] Department of Marine Engineering, Regional Maritime University, Accra, Ghana
[g] Department of Industrial Engineering, Dalhousie University, Halifax NS B3J 1B6, Canada

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ABSTRACT

In harsh environments, offshore oil and gas support operations are subjected to frequent logistics and supply chain operational disruption, due to harsh environmental factors with their associated risks. To capture these stochastic influential factors and support related decision making, it is helpful to develop a robust and dynamic probabilistic model.

The current study presents a proactive methodology that integrates the Pure-Birth Markovian process (PBMP) with the Bayesian network (BN) for the effective analysis of offshore logistics disruption risk. The PBMP captures the stochasticity in the failure characteristics of the engineering systems for estimating the time-evolution degradation probability. The BN explores the dynamic interactions among the most important offshore logistics influential factors to analyze the disruption risk in a harsh environment. The effects of influential factors' non-linear dependencies are propagated and updated, given evidence on the degree of disruption. The level of logistics disruption is further assessed using cost aggregation-based expectation theory. The theory explores the incurred cost/economic risk under different operational scenarios. The proposed methodology is tested on an offshore supply vessel operation to estimate the likely operational disruption risk in terms of financial loss in a harsh operating environment. The most critical influential functions are assessed to establish their degree of impact on the logistics disruption. At the upper bound probability of disruption occurrence, an economic risk/additional incurred cost of US$2.38E+05 with a variance (σ^2) of 3.05 $\times 10^9$ was predicted. The result obtained suggests that the proposed methodology is adaptive and effective for dynamic logistics disruption risk analysis in harsh offshore environments.

* Corresponding authors.
E-mail addresses: sadumene@mun.ca (S. Adumene), rabiul.islam@utas.edu.au (R. Islam).

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1. Introduction

Nomenclatures

BN	Bayesian network
PBMP	Pure birth Markovian process
PDF	Probability density function
H_s	Significant wave height
T_w	Zero crossing wave period
W_s	Wind speed
$\mathbb{E}[\cdot]$	Expectation operator
$Var\{C_d\}$	Variance of each cost element C_d
$Cov\{C_d, C_{d'}\}$	Covariance between C_d and $C_{d'}$
$\mathbb{P}(C_d)$	Probability of the loss element/scenario
$C_{1,........,}\ C_d$	Random variables for a given disruption scenario
$P_y(Y_i)$	Parent of variable X_i
$P(U)$	Joint probability distribution
$P(U\|E)$	Conditional probability
$(P_{ij}(t))_{i,j\in\mathscr{S}}$	Transition probability function
λ	Failure rate
$\mathscr{S}$	State space
$(q_{ij})_{i,j\in\mathscr{S}}$	Transition rate function

Marine and offshore logistics support vessels' transportation/operations play a crucial role in the sustainability of drilling and rescue support operations in the offshore oil and gas industry. The recent increase in oil and gas operations in the remote harsh offshore environments have triggered additional/associated risks in service delivery and operations of supply/support vessels. Safety plays an important role in every maritime operation due to the hostile operating environment, especially during remote offshore operations. For instance, in the sub-arctic and arctic regions, several logistics disruption risk factors, such as icebergs, fog, polar low, snowfall, navigation difficulty, limited competency, lack of critical equipment, and extreme temperature are predominant and contribute to logistics disruption (Afenyo et al., 2017; Khan et al., 2018). This may increase the likelihood of accidents during operations and impact the offshore support vessels' logistics/supply chain objectives. Several recent maritime accidents that induced logistics disruption have been reported; such as the case of container ship grounding in the Suez Canal and chemical explosion in the Port of Beirut. This neccessitate the development of a resilient supply chain and operational framework that will enhance logistics sustainability in harsh environments.

There is a need to better understand the interaction among the logistics strategy objectives, business strategy, and the contribution of technical and operational disruption risk factors for a sustainable upstream logistics operation of the offshore oil and gas industry. Ascencio et al. (2014) proposed a collative logistics framework for maritime support operations. The authors integrated the port logistics governance, port logistics operations model, and logistics management platform system to provide an improved decision-making framework for a port logistics supply chain structure. The model could predict the priority links based on the available infrastructure, resources, and information support systems for decision-making. Gutierrez-Alcoba et al. (2017) applied an optimal fleet composition model for offshore logistics support operations. The model captures fleet availability within the time horizon and operational optimization for recurring vessel scheduling in the harsh offshore environment. The model further captures the effect of weather constraints, such as wave height, visibility, and wind speed, for optimal vessel fleet decision-making. In another study (Vis and Ursavas, 2016), a simulation-based decision support model for logistics support modeling in offshore operations is proposed. The authors describe the critical parameters that affect the logistics weight and managerial logistics decision strategy in an offshore wind turbine operation. This includes the turbine characteristics, process characteristics, weather influences, pre-assembly strategy, performance measurement, and cost. This will provide managerial insight in critical logistics planning that will minimize the cost of investment and interruption.

Borch (2018) identified platform management strategy, input delivery request framework, platform cargo lists/order form, storage planning, ship co-ordination, loading/unloading, ship servicing, outbound, and inbound steaming as critical operational parameters in the field/upstream logistics management chain. The functionality of the technical parameters for offshore logistics operations may place a high safety demand on the vessel, especially in the remote harsh Arctic environment (Borch, 2018; Islam et al., 2018). This poses functionality challenges on board the ship, such as maintaining service speed and timely delivery, and the risk of collision with other ships. Others include complicated/imperfect maintenance processes and repairs, complicated ice removal from installations, poor winterization, emergency response challenges, and difficult vessel evacuation in remote harsh offshore operations (Aas et al., 2009; Rahman et al., 2020a; Arctic Council 2009; Borch, 2018). The reviewed models are inadequate to capture the dynamism and variability in the upstream logistics disruption risk influencing factors during Arctic operations.

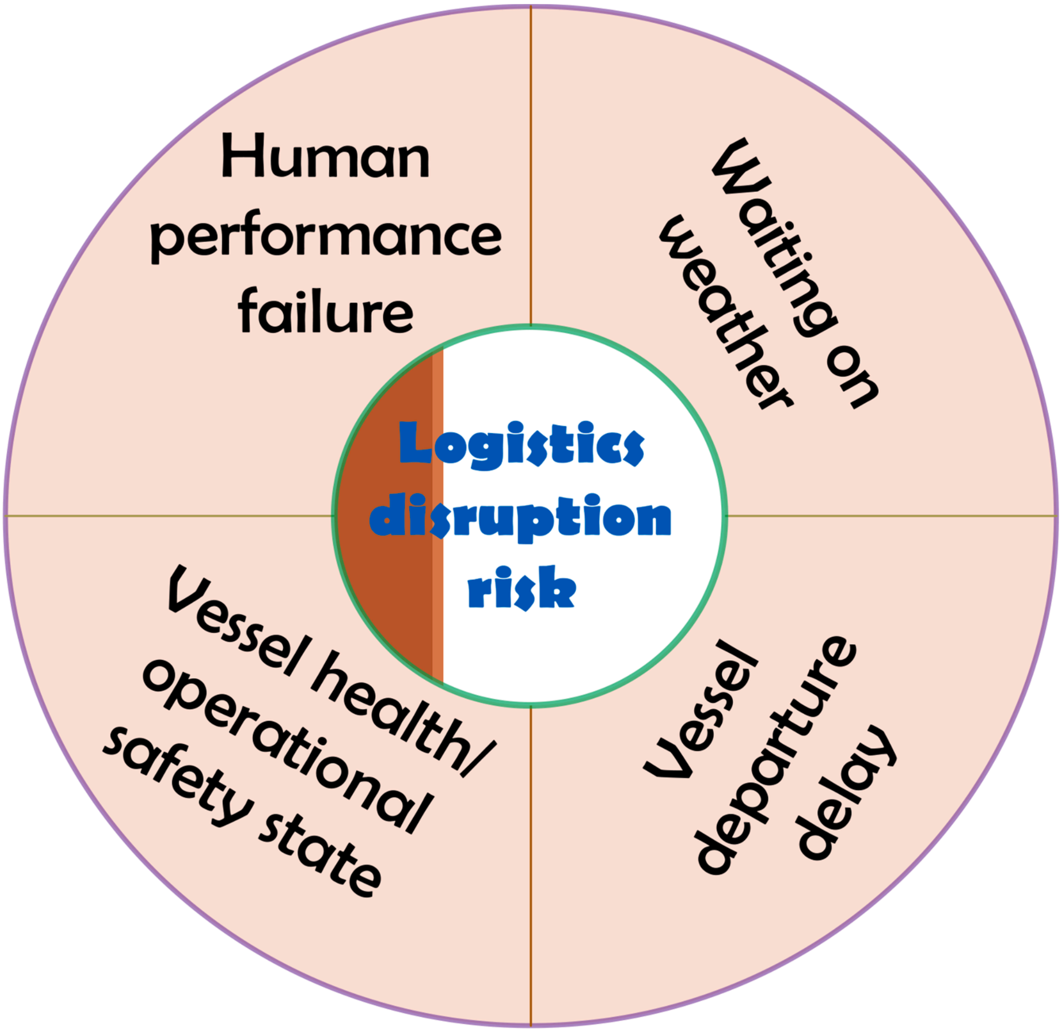

Fig. 1. Schematic diagram of the core logistics disruption risk influencing functions.

Furthermore, (Rahman et al., 2019, 2020b) proposed a fuzzy-based Fault Tree and Bayesian network (BN) for analysis of critical controlling factors of offshore logistics in the Arctic and sub-arctic zones. The models captured the various failure modes and their criticality for offshore emergency response (ER) vessel operations in harsh environments. These include technical system functionality, delay in vessel readiness, competencies, onboard operation, promptness, and the human factor. The model further considers conditional dependences of the failure risk influencing factors on emergency response (ER) operations in harsh offshore environments. Although the model provided a preliminary logistics risk framework for offshore operations, it focuses primarily on ER operations. The authors did not consider the dynamic degradation of the mechanical and technical systems (both operational and standby), even though this affects the timely response to the supply chain in harsh weather operations. Furthermore, HOSSAIN et al. (2020) developed an adaptive BN structure to capture the interdependencies among inland port infrastructure and its surrounding supply chain strategy. The authors identified environmental constraints and lack of responsive supply chain strategy as key to logistics disruption in maritime operations. Moreover, natural disasters induced logistics disruption in inland water transportation are environmentally dependent; this affect maritime transportation, especially in the Arctic waters (Goerlandt and Islam, 2021). The effect of upstream logistics disruption and strategic management objectives regarding the associated economic risk on supply chain design has not been investigated.

There is a need to capture the time-evolution degradation probability profile of the technical system together with the vital upstream logistics influencing parameters and their effects on the disruption risk in offshore supply vessel operations. Besides, the dynamic ocean parameters, such as waves and wind, can be represented using a dynamic discretized node or continuous nodes in the BN for a real-time probability estimation based on the metocean data of the region.

In addition, it is essential to capture critical disruption risk influencing factors that affect offshore service vessels' upstream logistics operations in high Arctic oil and gas fields. To capture these multifaceted disruption risk factors, it is useful to develop a multi-functional network that relates vessel preparedness, technical system functionality, human reliability, and upstream logistics/

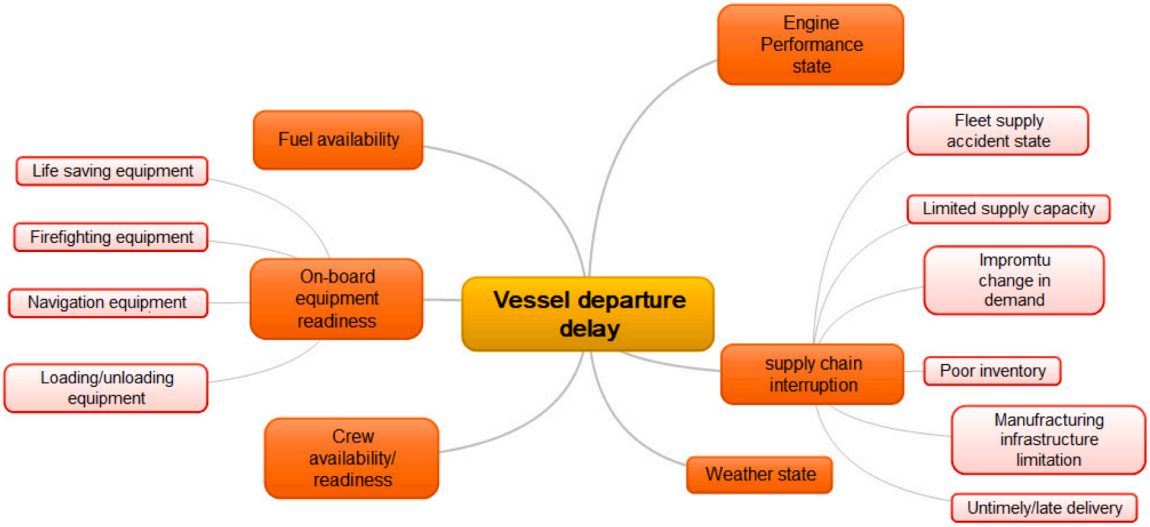

Fig. 2. Logical representation of the contributory factors to vessel departure delay.

supply chain strategy objectives for sustainable logistics operations and disruption risk prediction, especially for remote harsh operations.

The current research paper presents the development of a hybrid pure-birth Markovian process – Bayesian Network (PBMP-BN) model and demonstrates its novel application for upstream logistics disruption risk analysis in harsh offshore supply vessel transportation/ operations. The PBMP is used to estimate the time-evolution failure probability distribution for the mechanical and technical systems under a continuous-time homogeneous Markovian assumption. The BN encompasses the various disruption influencing factors and their non-linear dependencies for analyzing the overall risk. The model dynamically captures key elements that characterize the logistics disruption risk, and enables the analysis of their dominance effects in different operations, including loading, departure, transit, and unloading operations in harsh offshore environments.

The remaining sections of the paper are structured as follows: Section 2 introduces the logistic disruption influencing factors. Section 3 present the hybrid methodology for logistics disruption risk analysis. Section 4 describes the case study. Section 5 presents the results and discussion and finally, Section 6 concludes.

2. Overview of logistic disruption influencing factors for offshore support operations

The complexity in marine logistics and offshore support operations involves a multi-faceted operational demand and supply, which require a proactive logistics framework in order to sustain the operations. The logistics strategy plan may vary depending on location, cargo volume, routing, frequency of request, delivery time, environmental sensitivity, and laws and regulations (An et al., 2019; Borch, 2018; Lee and Cullinane, 2016). These factors affect the operational framework of a logistics supply chain for offshore supply vessels. For the present research, Fig. 1 depicts the adopted core logistics disruption risk influencing functions.

The following subsections briefly describe the influencing factors that define the core logistics disruption risk functions.

2.1. Vessel departure delay influencing factors

The logistics support in offshore operations consists of sequences of events and actions that form the supply chain framework for timely service delivery. The timely and uninterrupted voyage depends on the vessel's readiness and prompt departure (Malykhanov and Chernenko, 2015; Rahman et al., 2019; Wang and Meng, 2012). The level of logistics supports (supply chain process) is a function of timely delivery to offshore oil and gas platforms. Consideration should be given to identify vessel routing and various contributory factors that affect the timely departure of a supply vessel for a given supply chain process (Chima, 2007; Halvorsen-Weare and Fagerholt, 2017; Ishii et al., 2013; Li et al., 2012). It is essential to consider the critical factors that affect the stowage planning in a supply chain framework for offshore supply operations. These factors, such as the bulk cargo tank capability, vessel's deck space, crane capability, and vessel stability, could affect the loading/unloading operations and timely departure of the vessel. To better understand the interdependencies between the contributory factors, Fig. 2 shows the logical representation of these parameters as they affect the vessel departure delay function.

2.2. Human performance failure influencing factors

In offshore logistics supports, human reliability plays a critical role in sustainable supply chain operations. Human performance

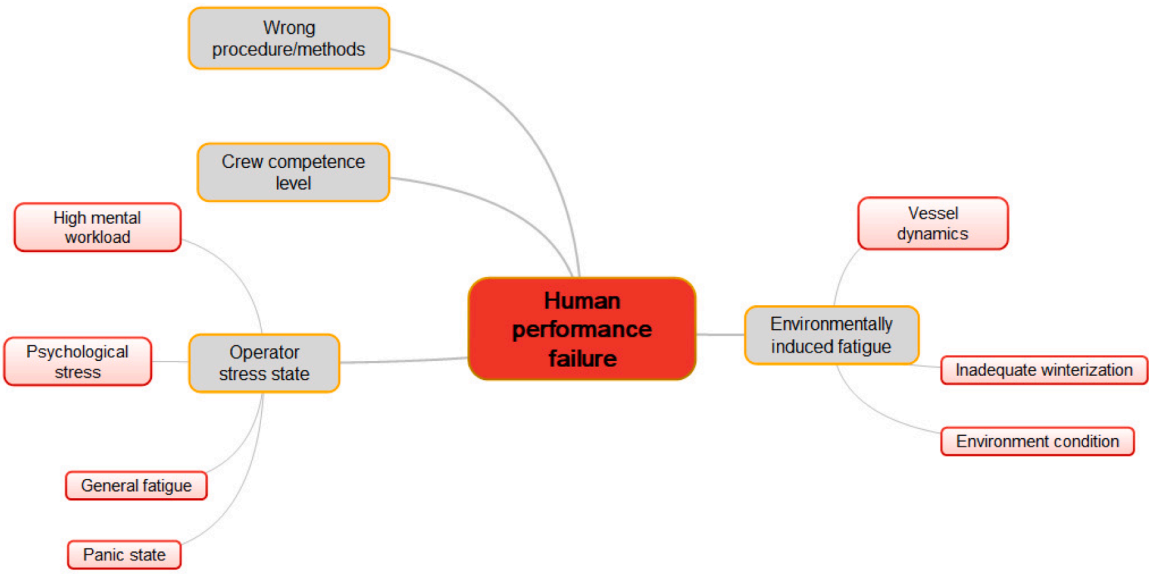

Fig. 3. Human performance failure influencing factors.

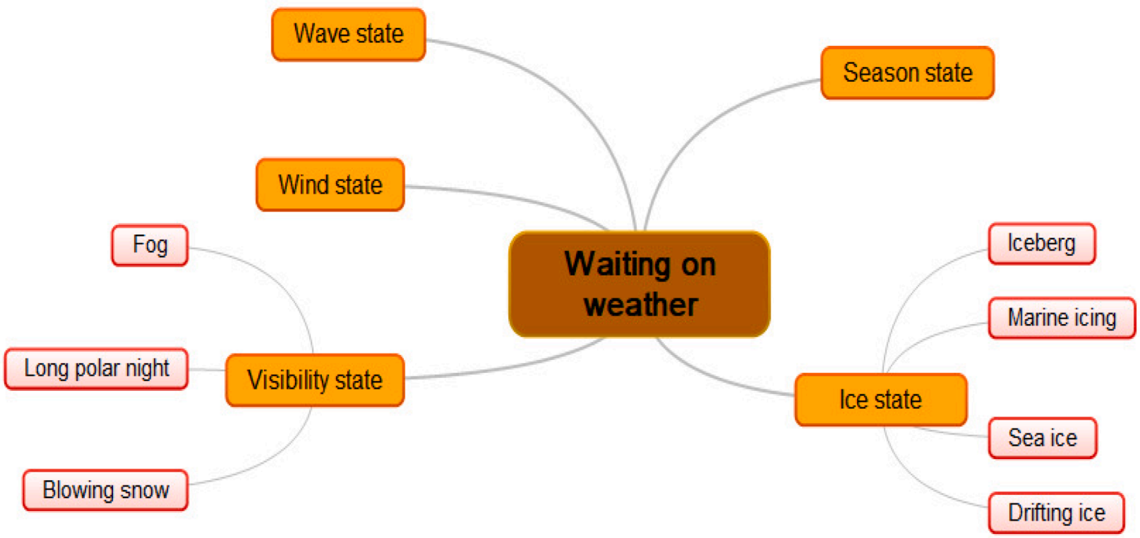

Fig. 4. Logical diagram of weather constraining factors.

relates to all the subsections of the supply chain framework, such as product design/manufacturing, packaging, transportation to the base/port, loading/unloading of the vessel, vessel maintainability, manning of the vessel, navigation, and operational decision making (Islam et al., 2018a; Yazdi et al., 2021; Zarei et al., 2019). Based on this, the predisposing factors for human performance in harsh environment offshore supply operations are shown in Fig. 3.

2.3. *Waiting on weather influencing factors*

The offshore supply operations in arctic waters pose a high risk of disruption due to the harsh environment. The harshness of the arctic waters is due to the prevailing factors, such as blowing snow, fog, long polar nights, marine ice, and icebergs, among others (Afenyo et al., 2017; Khan et al., 2018). These factors affect and cause a delay in sailing, loading/unloading operations at port, sea, and offshore platforms. The result of the delay or waiting on weather causes a disruption in the logistics process and the overall supply chain framework. A better understanding of the degree of impact of these factors on any offshore supply chain processes and operations is crucial for robust estimation of the logistics disruption risk. Based on the information in the above cited sources, Fig. 4 presents a logical representation of the influential factors related to waiting on weather.

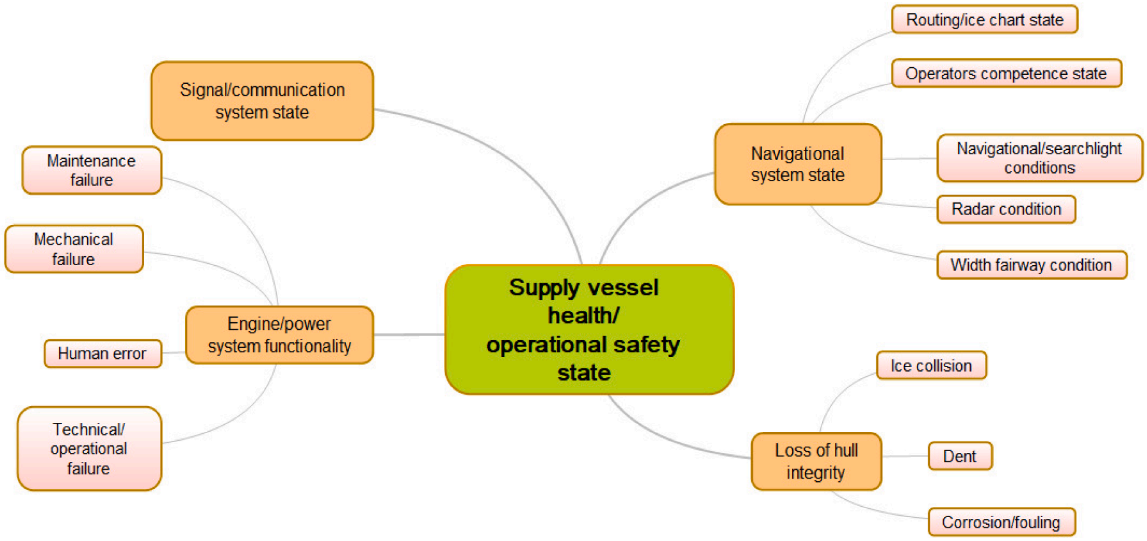

Fig. 5. Vessel health/operational safety state influencing factors.

2.4. *Supply vessel health/operational safety state contributory factors*

Offshore logistics operations in the harsh arctic environment demand high performing systems and vessels. The systems/vessel performance is dependent on their health state during the stages of operations. The likely failure states that may affect the health of the vessels include the integrity of the hull structure, engine and power system functionality, and navigational aid systems, among others (Nwaoha and Adumene, 2019; Rahman et al., 2020b). To capture these critical factors for the disruption risk analysis, a logical structure is shown in Fig. 5.

3. A hybrid methodology

The offshore supply vessel provides various services and operations within the clusters of the oil fields in the harsh offshore environment. These operational complexities, including installation support, cargo supply and transport and emergency response, possess critical challenges, especially in harsh arctic environments (Aas et al., 2009). It is important to obtain a better understanding of the effect of the influential factors on every sub-nodes of the logistics process for offshore oil and gas operation support in arctic waters. For this, it is vital to adopt a dynamic and robust methodology. Fig. 6 provides the procedure for the proposed hybrid methodology for logistics disruption risk analysis. The details are further outlined and presented in the steps below.

Step 1: All marine and offshore operations have inherent risk. Therefore, it is important to define the type of logistics support operations and the operational characteristics needed for the given task. The definition or classification of the operations will provide vital information about the required resources to execute the tasks safely. For instance, the logistics operation may be raw material supply operation, personnel supply operation or installations support operation. The duration and routing of the operations and material outsourcing via supply chain planning based on offshore platform demand need to be defined. This will help to properly link the sub-nodes of the logistics framework for the successful execution of the task.

Step 2: Having defined and classified the operations, critical influential factors and resources must be identified. This captures the logistics disruption influencing factors such as the vessel tonnage and health states, human resources (crew expertise), material availability and inventory, systems failure states (failure modes), and the fleet management. For mechanical system and vessel structural failure, the failure mode and effect analysis (FMEA) tool is adopted to identify likely failure modes of the vessel subsystems during operation (Nwaoha and Adumene, 2019; Rahman et al., 2019; Wan et al., 2019). The essence of the applicability of the probabilistic tool (FMEA) is to provide risk-based information on the health state of the systems for proactive intervention prior to departure from port and/or at sea. For example, Fig. 1, Section 2 of the manuscript, outlined likely vital logistics disruption functions for offshore logistics support operations in the arctic environment.

Step 3: The identified logistics disruption functions are further developed into logical structures based on the interconnectivity of their essential elements, as shown in Figs. 2-5, Section 2. The basic predisposing factors that affect the offshore supply vessel logistics are captured in the logical frameworks as shown. In most cases, fault trees analysis (FTA) may be used to logically represent the interconnectivity among the basic influencing factors and the top event of the logistics framework (Adumene and Okoro, 2020; John and Osue, 2017; Rahman et al., 2019). A maple graph is used in this study to represent the logical interconnectivity among the basic logistics disruption influencing factors.

Step 4: The offshore supply vessel operation in arctic waters is exposed to harsh ocean environments that lead to degradation of the subsystems, hull structure, and over system performance. Most importantly, the mechanical systems may suffer multi-state failure

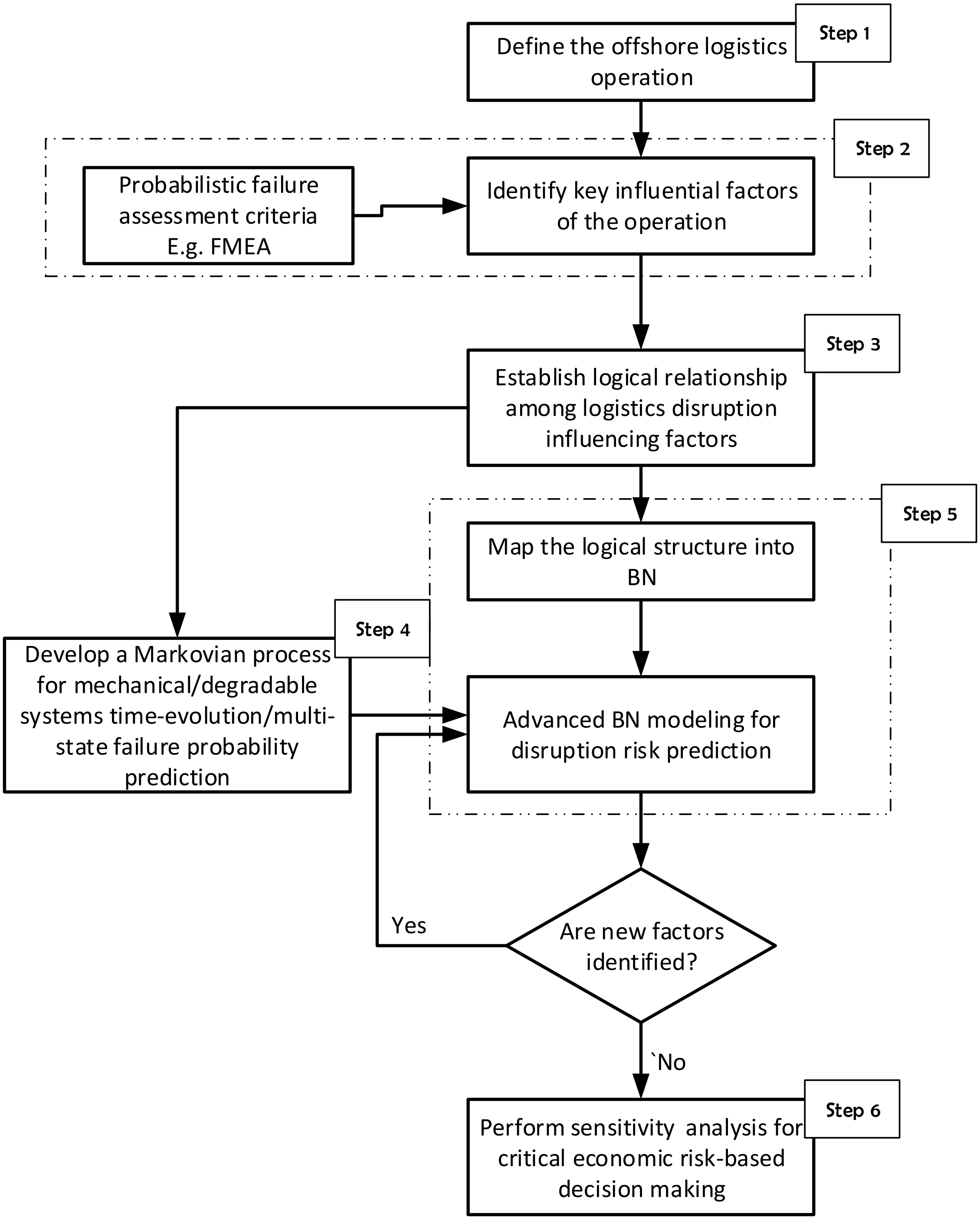

Fig. 6. An algorithm for offshore supply vessel logistics disruption risk analysis.

characteristics. This needs to be captured for accurate estimation of the failure profile of these factors over time. To capture the latent failure or degradable state (partial failure) of .the systems over time and for condition monitoring, the PBMP has shown promise (Adumene et al., 2020a; Arzaghi et al., 2020; Nitonye et al., 2020). The failure profile characteristics and the associated mathematical formulation is built based on the stochastic Markovian assumption. The equipment functionality failure such as the main engine, propulsion shaft, and gearbox degradation can be modeled using the multi-state (fully operational, pseudo-operational, and failed) Markovian formalism. Fig. 7 shows the pure-birth-continuous time-homogeneous Markovian process, such that for a given stochastic process $(Y(t))_{j\geq 0}$, its homogeneity occurs if all $0 < t_1 < \ldots < t_n,\ i_0, i_1, \ldots.., i_n \in \mathscr{S},\ \cap\mathscr{S}\ \mathbb{N}$ and includes (Arzaghi et al., 2020; Nitonye

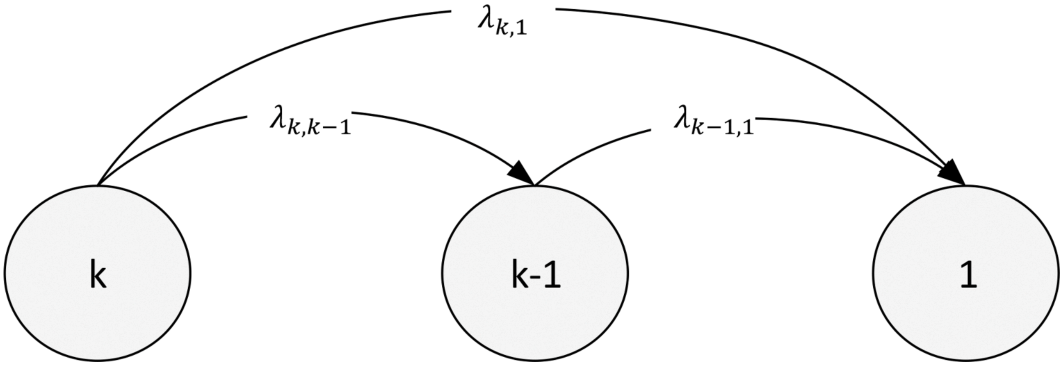

Fig. 7. State-transition diagram of the PBM process for degradable subsystems.

et al., 2020):

$$P\{Y(0)=i_0,\ Y(t_1)=i_1,\ldots\ldots.,\ Y(t_n)=i_n\} \tag{1}$$

Considering the Chapman-Kolmogorov formulation for a PBM with a state space $\mathscr{S}$, rate $(q_{ij})_{i,j\in\mathscr{S}}$ and transition probability function $(P_{ij}(t))_{i,j\in\mathscr{S}}$ gives:

$$P_{ij}(t+s) = \sum_{k\in\mathscr{S}} P_{ik}(t)P_{kj}(s) \tag{2}$$

If the formulation is conditioned on the distribution of $Y(t)$, we have:

$$P_{ij}(t+s) = P(Y(t+s)=j|X(0)=i) \tag{3a}$$

$$= \sum_{k\in\mathscr{S}} P(Y(t+s)=j|Y(t)=k)P(Y(t)=k|Y(0)=i) \tag{3b}$$

$$= \sum_{k\in\mathscr{S}} P(Y(s)=j|Y(0)=k)P(Y(t)=k|Y(0)=i) \tag{3c}$$

$$= \sum_{k\in\mathscr{S}} P_{kj}(s)P_{ik}(t) \tag{3d}$$

where the time is exponentially distributed with $\nu_i = \sum_{j\in\mathscr{S}} q_{ij}$ from state i to state j, and q_{ij} matrix is expressed by Eq. (4), with λ indicating the failure/degradation rate of the subsystems.

$$\text{Generator matrix} = Q = \begin{vmatrix} -(\lambda_{k,k-1}+\lambda_{k,1})(t) & \lambda_{k,k-1}(t) & 0 & \cdots \\ 0 & -\lambda_{k-1}(t) & \lambda_{k-1,1}(t) & \cdots \\ 0 & 0 & (\lambda_{k,1}+\lambda_{k-1,1})(t) & \cdots \\ \vdots & \vdots & \vdots & \vdots \end{vmatrix} \tag{4}$$

This formulation is applied to modeling the failure profile of the main propulsion subsystems. The results serve as input data to the BN structure in step 5 of the study.

Step 5: The logical graph is mapped into the BN structure. The essence is to capture the dynamic non-linear interactions among the influential logistics disruption factors. BNs are well known machine learning formalism that has demonstrated high performance for stochastic modeling of complex systems under uncertainty. It implements a dependency structure via a directed arc graph suitable to depict for multi-state and multi-dimensional configurations (Adumene et al., 2020a; Chandrasekaran, 2015; Islam et al., 2018b). Recent studies that focus on the application of BN in maritime logistics and supply chain-related risk have been reported in the referenced literature (Ascencio et al., 2014; Cao et al., 2019; Goerlandt and Islam, 2021; Hänninen et al., 2014; HOSSAIN et al., 2020; Hosseini and Ivanov, 2020; Lu et al., 2020; Nguyen et al., 2021; (Rahman et al., 2020b); Zarei et al., 2019; Zhang et al., 2020).

Using BN for the logistics disruption risk modeling, the dependencies among the vital factors can be represented vertically or horizontally. The vertical representation describes the dependency of the intermediates nodes on the cause nodes, while the horizontal representation captures the mutual dependencies)(Adumene et al., 2021a,b; Jiang and Lu, 2020; Ung, 2021; Wan et al., 2019; Wu and Law, 2019; Yazdi and Kabir, 2017; Yu et al., 2021). Given a set of random variables $U = \{Y_1,\ldots\ldots., Y_n\}$, the chain rule and joint probability distribution P(U) based on conditional independence are represented by Eq. (5) (Jensen and Nielsen, 2007).

$$P(U) = \prod_{i=1}^{n} P(Y_i|P_y(Y_i)) \tag{5}$$

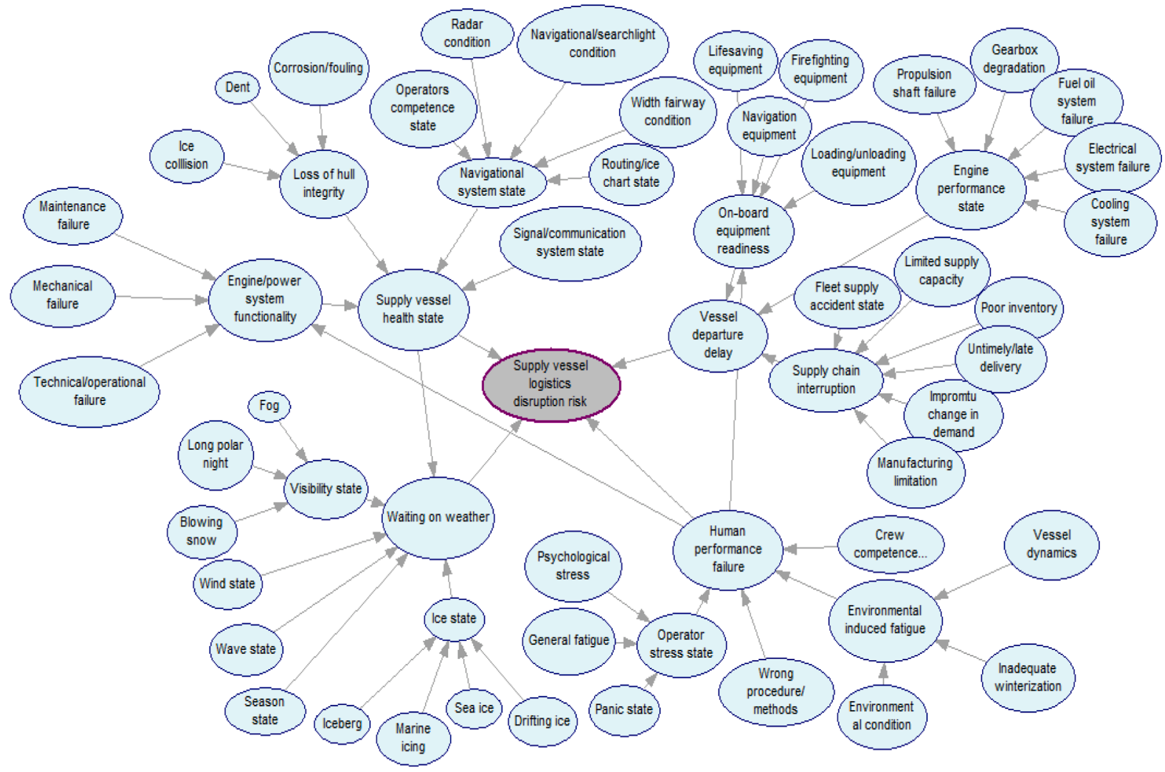

Fig. 8. Schematic of the BN model for offshore supply vessel logistics disruption risk.

where $P_y(Y_i)$ represents the parent of variable Y_i and P(U) describes the joint probability distribution of the variables. The probability of Y_i is expressed by Eq. (6).

$$\mathrm{P(Y_i)} = \sum_{\mathrm{U \backslash Y_i}} \mathrm{P(U)} \tag{6}$$

where the summation is taken over all the variables except Y_i.

The BN is updated based on Bayes' theorem. The theorem enables the structure to update the prior probability of the influential factors given new information (called evidence E) to produce the consequence probability (called posterior).

The BN forward (predictive) analysis, as shown in Fig. 8, describes the likelihood of occurrence of any node of the structure based on the prior probabilities of the root nodes and the conditional probability that captures each node's conditional dependence/ interactions.

The logistics disruption risk node is categorized into high, moderate, and low-risk states to implement the BN model, depending on the duration of the delay and cost implication due to operational interruption both at the port and at the platform. In contrast, the general influential factors, as shown in Fig. 8, are expressed in two states: "Present" and "Absent", or "Yes" and "No" or "Success" and "Failure", which describe the state of the positive assertion of a cause of a specific variable. The cause-effect relationships are built into the structure based on the conditional probabilities. The conditional probabilities define the dependency among the influencing parameters. The conditional probabilities for the intermediate node and the child node are created by exploring the dynamic interaction among different influencing factors of logistics disruption risk. Also, part of the information on the prior probabilities of the influential factors is derived from historical data, literature, and subject expect opinions. The logistics disruption risk profile is developed by inputting the prior probabilities of these influential factors and the conditional probabilities.

Furthermore, the environmental elements (i.e., the wind, waves, ice) data from the (DFO-MPO, 2018) are used to categorize the nodes based on the significant wave height, $H_s(m)$, zero crossing wave period, T_w (s) and the wind speed W_s (m/s). The significant wave height describes the mean height of the highest third waveform and under zero up-crossing wave period. The significant height is evaluated using Eq. (7) (Tann, 1976). Similarly, the zero-crossing wave period that describes the time interval between two zero up-crossing waveforms can be evaluated using its mean value, by Eq. (8).

$$H_s = \frac{1}{N}(H_{2N+1} + \ldots + H_{3N}) \tag{7}$$

where the waves' heights $H_1, \ldots\ldots, \ldots\ldots., H_{3N}$ are expressed in ascending order based on the available data.

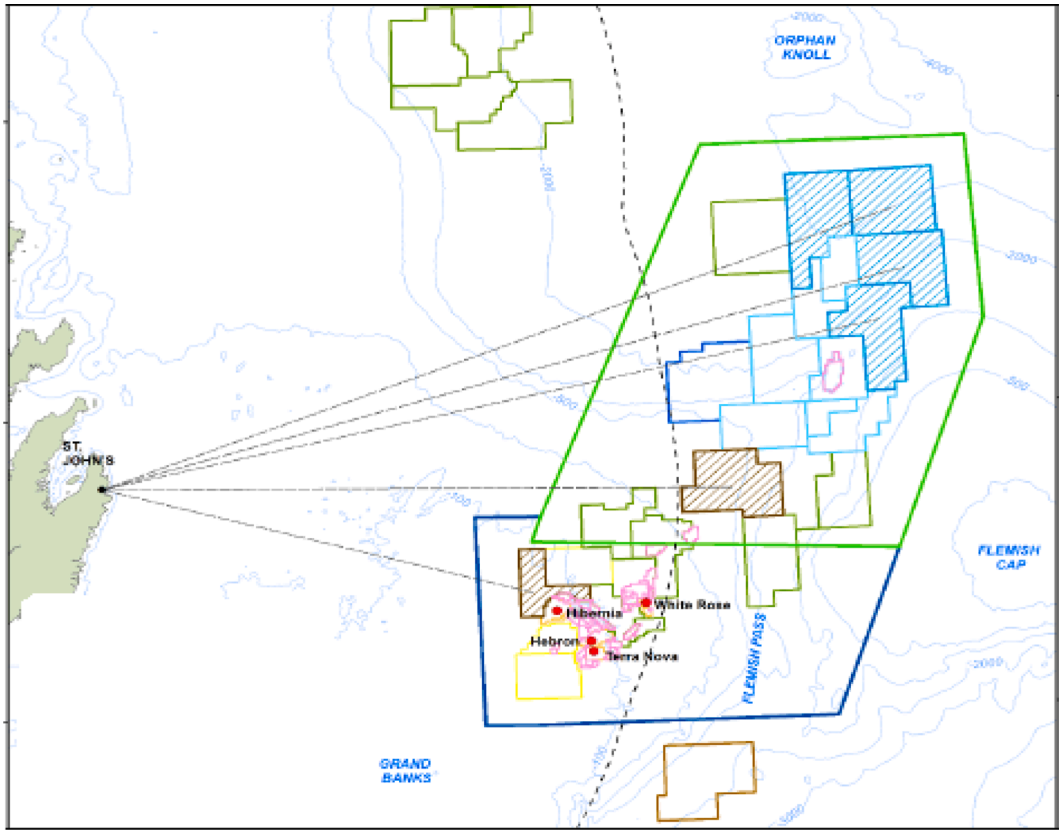

Fig. 9. Potential aircraft and supply vessel transit routes for Flemish Pass fields (adopted from Statoil, 2017).

$$T_w = \frac{t \times \ 60}{No.\ of\ zero\ up - crossing\ waves\ from\ availabe\ data}\ (sec) \tag{8}$$

where t is the recorded duration in minutes.

To estimate the prior probabilities of the waves' and wind effects based on the significant wave heights and wind speed, Eq. (9) and Eq. (10) are adopted. Details of the application are shown in section 5.

$$P(H_s) = \frac{Number\ of\ wave\ heights\ that\ occurred\ in\ each\ range}{Total\ number\ of\ wave\ heights\ that\ occurred(count)} \tag{9}$$

$$P(W_s) = \frac{Number\ of\ wind\ speeds\ that\ occurred\ in\ each\ range}{Total\ number\ of\ wind\ speeds\ that\ occurred(count)} \tag{10}$$

Step 6: To examine the degree of influence of the vital factors on the disruption risk and its prediction, a sensitivity analysis is carried out by placing evidence on the pivot node. The essence is to identify and monitor, in terms of relative importance, the critical input parameters' effects on the risk profile. Several approaches for sensitivity-based analysis have been reported in the literature ((Adumene et al., 2020b); Afenyo et al., 2017; Pearl, 1988; Shabarchin and Tesfamariam, 2016). However, a diagnostic technique is adopted for the research analysis.

To capture the effect of the disruption function parameters and the harsh operating environment in terms of cost, an economic risk profile is developed for the financial costs due to logistics disruption and operational interruption. The economic risks are modeled using the loss/cost aggregation technique shown in Eq. (11) and Eq. (12) ((Adumene et al., 2021a); Epstein, 2012; Hashemi et al., 2015), respectively. The cost elements are defined by their probabilistic characteristic for economic risk profiling.

$$\mathbb{E}[C_E] = \sum_{d=1}^{D} E[C_d] \cdot \mathbb{P}(C_d) \tag{11}$$

$$Var[C_E] = \sum_{d=1}^{D} Var(C_d) \cdot \mathbb{P}(C_d) + 2\sum_{d=1}^{D} \sum_{d'<d}^{D-1} Cov(C_d, C_{d'}) \tag{12}$$

where $\mathbb{E}[\cdot]$ is the expectation operator; $Var\{C_d\}$ defines the variance of each cost element C_d; $Cov\{C_d, C_{d'}\}$ symbolizes the covariance between C_d and $C_{d'}$; $\mathbb{P}(C_d)$ refers to the probability of the cost element/scenario (disruption) occurrence; $C_1 \cdots C_d$ are the random variables that represent the elements of a given disruption scenario, and $d = 1, \cdots\cdots, D$ indicates the number of disruption/operational interruption scenarios. The cost elements of the vessel operations are defined based on the day rates. The vessel lease cost consists of the mobilization cost, daily finance costs, daily operating costs, and the daily return on investments. The operational cost primary components/elements include labor, maintenance, fuel, insurance, and administration (Kaiser, 2015). These cost elements are dynamic variables and may be defined by their probabilistic characteristics to predict the economic risk using expectation probability theory.

4. Case study

The proposed logistics disruption risk model is demonstrated for offshore oil exploration support vessel operations in the Grand Banks and in extension, the Flemish Pass Basin (Rahman et al., 2020b). These locations show similar metocean characteristics that define remote arctic offshore operations . For instance, the Flemish Pass oil Basin is located about 480 km offshore from St. John's, Newfoundland and Labrador, with a water depth range of 500 to 3000 m (Rahman et al., 2020b; Nalcor Energy 2017). The Harshness index and iceberg challenges for these locations are critical to the survivability of the oil and gas infrastructures and operations (Arif et al., 2020; Rahman et al., 2020a; Nalcor Energy 2017). The environmental elements (i.e., the wind, waves, ice, current) data from the DFO-MPO (2018) is used to categorize the nodes based on the significant waves height, $H_s(m)$, zero crossing wave period, T_w (s) and the wind speed W_s (m/s) for the study location. The offshore support logistics operations for these terrains frequently experience interruption. This affect the operation and the sustainability of the oil field development. Fig. 9 shows the potential aircraft and supply vessel routing for these locations of study.

The probability data for the influential disruption functions were assessed based on a comprehensive literature survey. The vessel departure delay and supply chain interruption contributory factors probability were assessed from the referenced literature (Afenyo et al., 2017; Hosseini and Ivanov, 2020; Kum and Sahin, 2015; Sakib et al., 2021; Yazdi et al., 2020). The human performance failure basic parameters' data were obtained from the reference literature (Islam et al., 2018b; Rahman et al., 2019;(Rahman et al., 2020b)). The information of waiting on weather contributing parameters was extracted from the literature (Khan et al., 2018; Rahman et al., 2019). The input probability data used in the BN structure for the supply vessel health state influencing parameters were assessed from the works of (Jia and Zhang, 2021; Necci et al., 2019). The vessel leasing and operating cost elements for the research analysis were extracted from the referenced literature (Borthen et al., 2019; Kaiser and Snyder, 2012; Kaiser, 2015; Stålhane et al., 2016).

The Markovian stochastic process is used to model the propulsion system degradation, gearbox degradation, fuel oil system failure and cooling system failure. For the analysis, a set of transition matrices is adopted with an assumed prior probability distribution $\pi = [1\ 0\ 0]$. The essence is to define the state of the systems at the beginning of the voyage as fully operational. The system's performance will gradually change due to deterioration as the period of operation increases without replacement. The stochastic degradation process of the system is captured in the failure profile generated from the Markovian process for the period under consideration. For the model application the following assumptions are made:

i) The engineering systems are treated as degradable systems under a time-homogeneous Markovian assumption.
ii) The influential functions are defined by their basic elements and non-linear interactions.
iii) The characteristic offshore supply vessel is of deadweight 2500 tons, a day rate of $25,000/day, and operational cost of $8000/day.
iv) For a typical speed of 10 knots, a selected additional distance of 50 nautical miles from the port increases the day rate by $11,500 per trip.
v) The cost elements are assumed to be uncorrelated and normally distributed, with a 2% yearly inflation rate.
vi) The logistics disruption risk is categorized as High risk for an operational interruption for the period greater than one week: Moderate risk is taken as an operational interruption for the period greater than or equal to four days but less than one week. Low risk is for an operational interruption for the period less than four days.
vii) The additional cost elements/economic risk aggregation utilizes the regression formulation proposed in the reference literature (Kaiser and Snyder, 2012; Kaiser, 2015).

5. Results and discussion

The current research developed an integrated dynamic methodology that simultaneously captures the logistics parameters, their interdependencies, and the degradation potentials of the mechanical systems for logistics disruption risk prediction in arctic offshore support operations. The marine operations are defined to understand the associated failure scenarios, and the influential critical factors are identified. These parameters are modeled probabilistically, and their effects are analyzed using an adaptive Bayesian analysis.

5.1. Probability prediction based on the Markovian process and metocean data

The stochastic degradation process of the main propulsion subsystems is modeled based on their prior probability distribution and the transition probability matrix. The gearbox deterioration transition probability matrix is adopted from (Li et al., 2019), while other

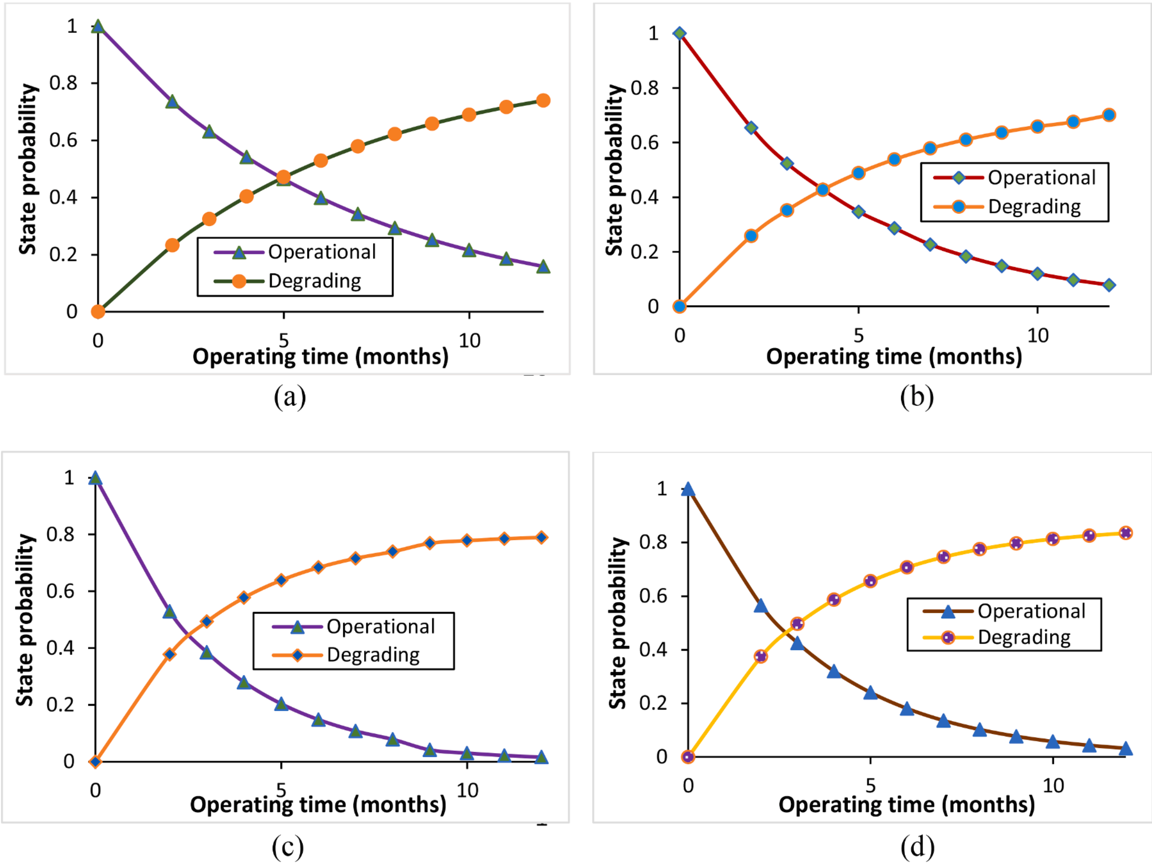

Fig. 10. Markovian process analysis for (a) Gearbox, (b) Propulsion system, (c) Fuel oil system, (d) Cooling system.

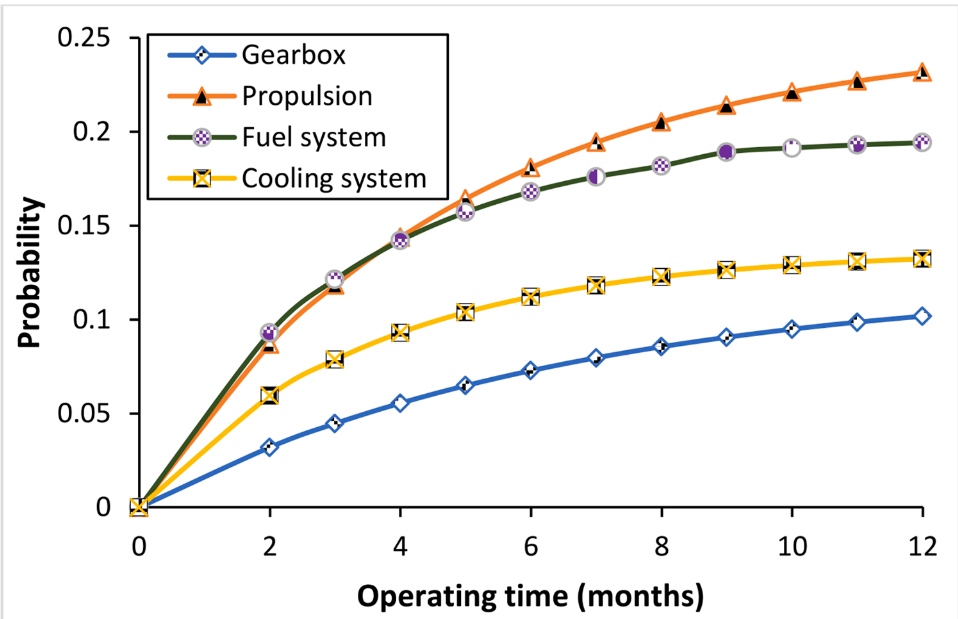

Fig. 11. Failure probability prediction with operating time in a harsh environment.

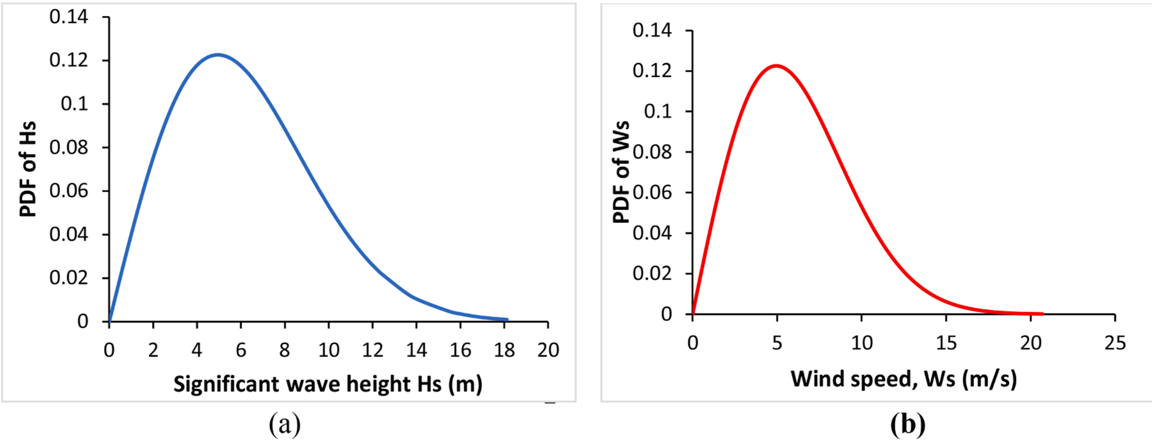

Fig. 12. Probability density function for: (a) significant wave height, (b) wind speed.

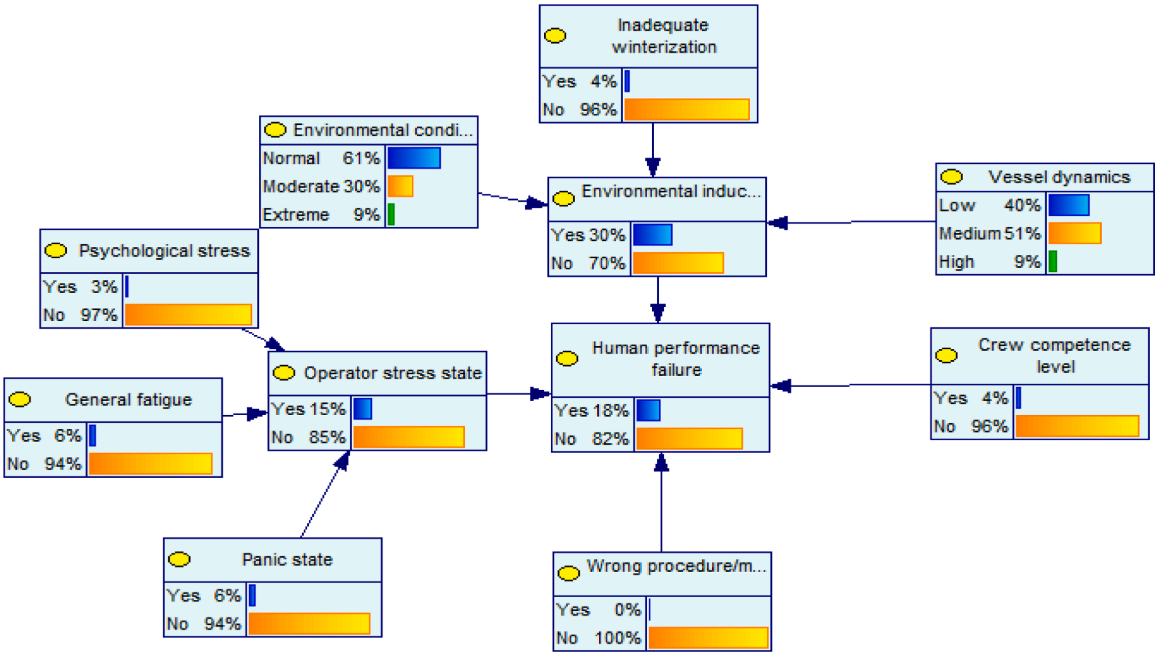

Fig. 13. Parametric learning of the BN structure for human performance function.

subsystems' transition probability matrix is evaluated based on the mathematical formulation presented by (Nitonye et al., 2020). The predicted failure profile of the subsystems based on Eq. 3 for the period under consideration is presented in Fig. 10. At each incremental time step, a probability distribution for the subsystems' states is estimated. The probability of failure can be estimated from the system state profiles, as shown in Fig. 11.

The result of the pure-birth Markovian process describes the degradation process of the mechanical systems under a harsh operating environment. The operational state and the degrading state are plotted together, as shown in Fig. 10, to illustrate the change in the performance of the subsystems over time. The results provide condition monitoring tools for setting criteria that will aid proactive integrity management of the systems. As presented in Fig. 10(a), the intercept depicts a critical point that could result in more than a 50% drop in the system functionality. This is also represented in Fig. 10(b)-(d), respectively. The subsystem failure probabilities for the period are extracted from Fig. 11 and used as input data for the BN parametric modeling.

To estimate the probability of wave and wind loads effects, the metocean data for the study location is used. The DFO-MPO (2018) data is used for the sea state data partitioning, and the probability is evaluated based on Eqs. (7)-(10). The probability density function (PDF) of the estimated probability is shown in Fig. 12. This forms the sea state (waves and wind) probability envelope for the period of operation and analysis. The predicted probabilities from the PDFs serve as input data for the BN modeling in Sections 5.2 and 5.3.

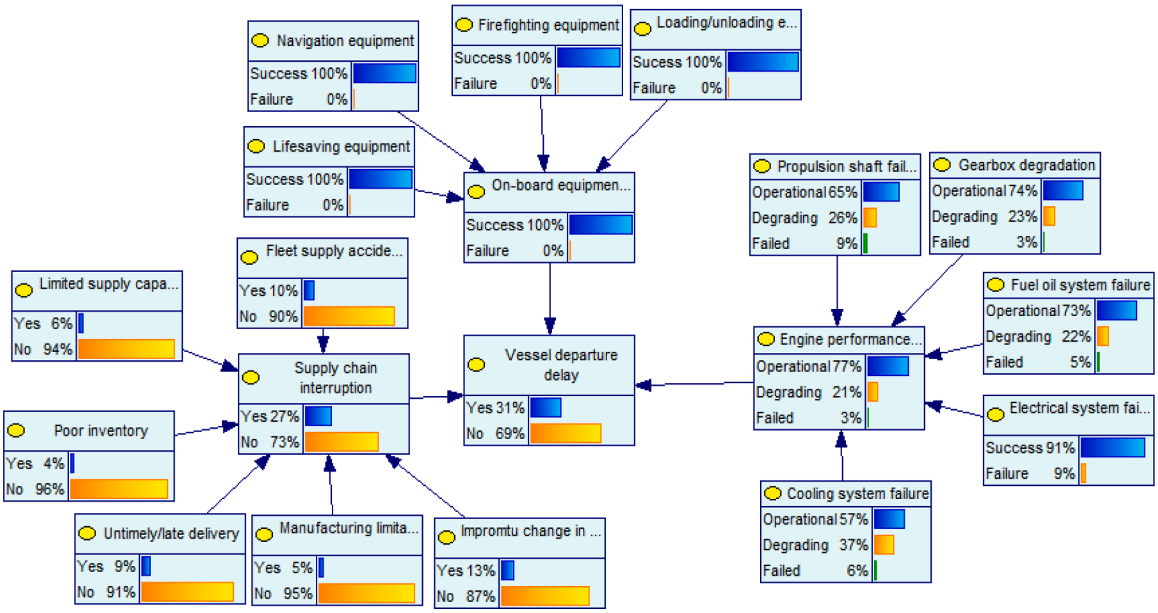

Fig. 14. Parametric learning of the BN structure for vessel departure delay function.

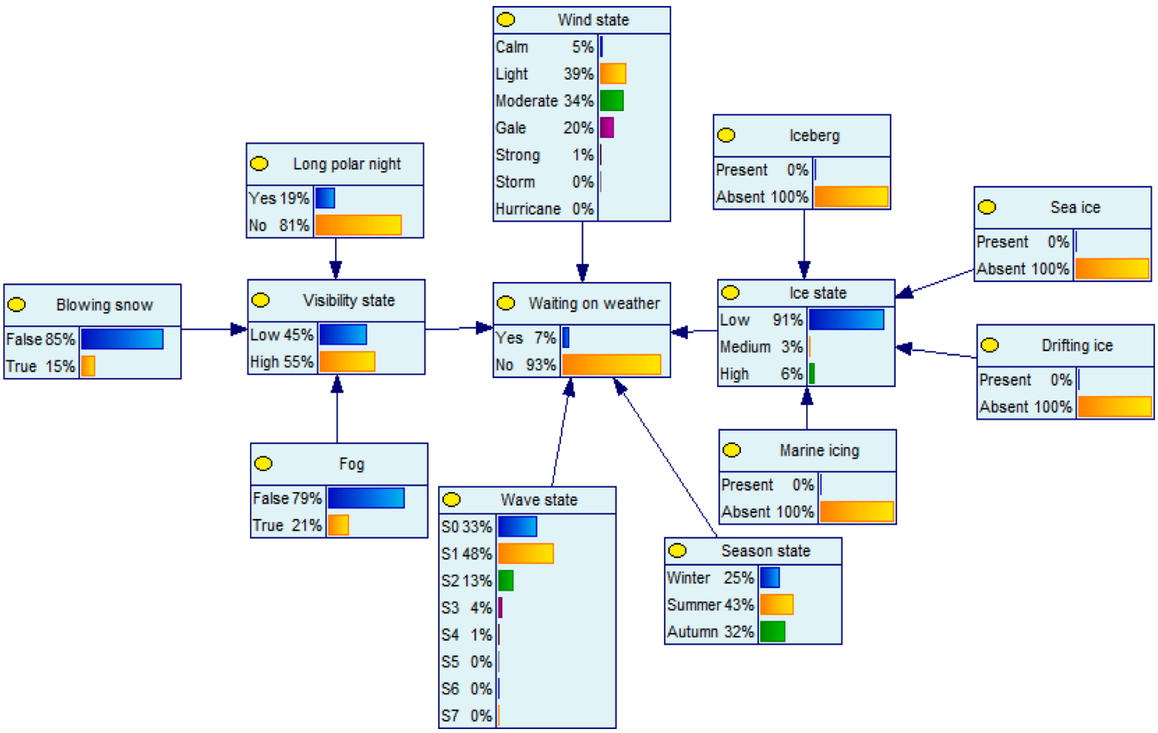

Fig. 15. Parametric learning of the BN structure for waiting on weather function.

5.2. Logistics disruption functions' modeling considering non-linear dependencies

The core logistics disruption influential functions are modeled based on the predefined probabilistic properties of the basic events. A novel BN structure is developed to depict the dependencies and interactions among the common parameters for estimating their probability of occurrence. The degree of influence of the various basic elements for each of the disruption functions is predicted. For instance, in Fig. 13, the operator stress state and environmental induced failure are dependent on other basic parameters that

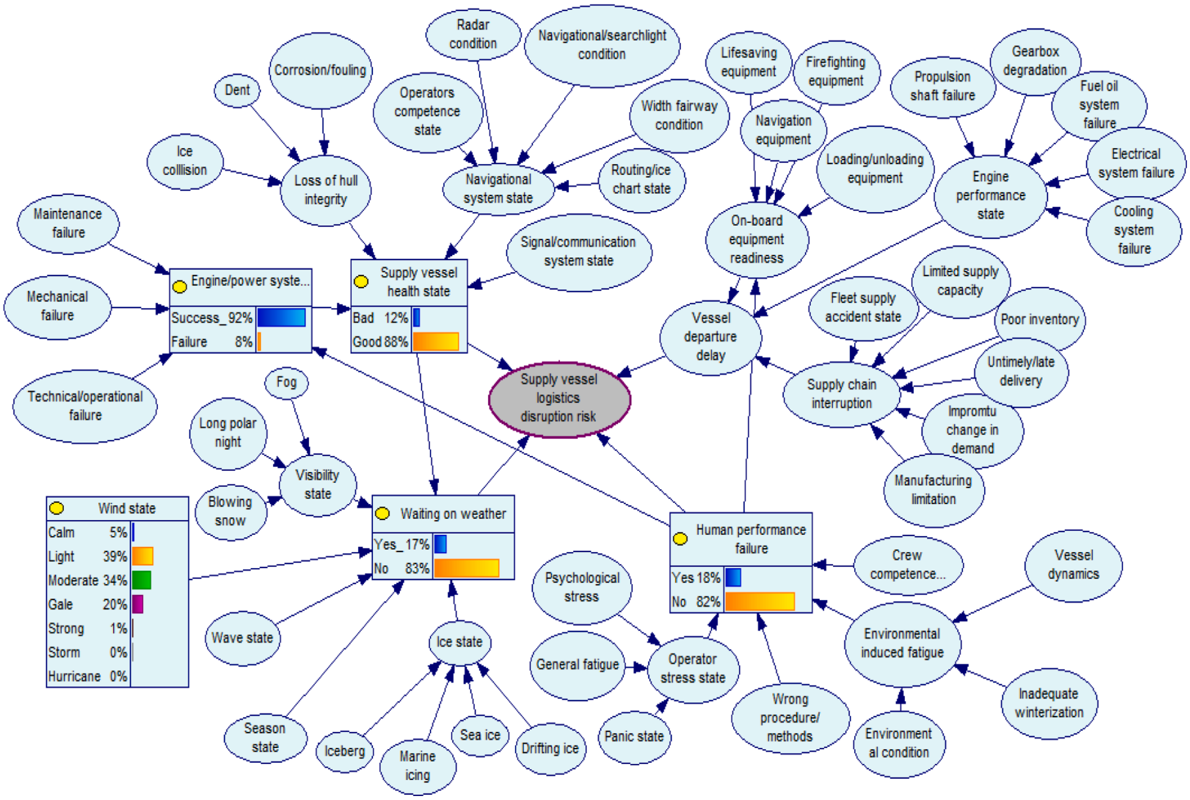

Fig. 16. BN structure for logistics disruption risk prediction.

characterize the operating state during the voyage and the physiological state of the operators/crew onboard. Moreover, the belief of the level of interactions among these parameters is propagated to the human performance failure node in the forward analysis. Under the prevailing operating state, a likelihood of 0.184 was estimated for human performance failure.

Furthermore, the logistics/operational interruption as a result of vessel health state affects the offshore support logistics/supply chain strategy. This is dependent on the engine performance state, health of the vessel, and availability of supply. The supply chain interruption may occur due to poor inventory or late delivery, among other causes. The BN structure that captures these interactions is shown in Fig. 14. It can be seen that the input parameters of the engine performance nodes predicted by the pure-birth Markovian process and the supply chain interruption play a crucial role on the departure delay node. Based on the parametric learning of the structure, a probability of occurrence of 0.306 is obtained for the vessel departure delay. Also, the future likelihood of occurrence can be estimated as a function of the time-evolution failure characteristics of the engine subsystems, as shown in Fig. 11. The novel application of the PBMP for the engine performance state/condition monitoring is one of the contributions of the proposed approach.

The harsh environment and its elemental constraints play a key role in offshore supply chain operations. In most complex logistics nodes where the vessel serves multiple platforms, delay due to weather can pose additional cost on the vessel management, as well as emergency production shutdown due to delay in spare part supply. The associated downtime for such operations could vary based on the distance between the serviced offshore platform clusters. This operation becomes more critical in remote harsh arctic operations that are exposed to unstable environmental parameters and limited data availability for operational predictions. Fig. 15 shows the BN structure built to capture the effects of these environmental parameters on the waiting on weather node, considering dynamic interactions among basic parameters. For remote harsh arctic operation, emphasis is placed on the metocean data, and their degree of impact is predicted. The probabilistic data for the wind and waves parameter were extracted from the results in Fig. 12, Section 5.1.

The result shows a likelihood of 0.066 for the waiting on weather node during the parametric learning of the structure. By placing evidence on the strong wind and the maximum wave height (S_4), a likelihood of 0.122 is estimated. This represents a 45.9% increase in the likelihood of occurrence of the waiting on weather node. For the predefined operating condition, the effects of the basic elements on the weather constraint can be predicted from the developed BN structure.

5.3. Dynamic logistics disruption risk estimation

The influential core functions of logistics disruption in harsh offshore support operations and their associated influencing factors are represented in Fig. 16. The BN structure captures the interactions among the basic failure elements for the overall disruption risk estimation for the case study. The essence is to understand the impact of the various functions/actions for a robust economic risk

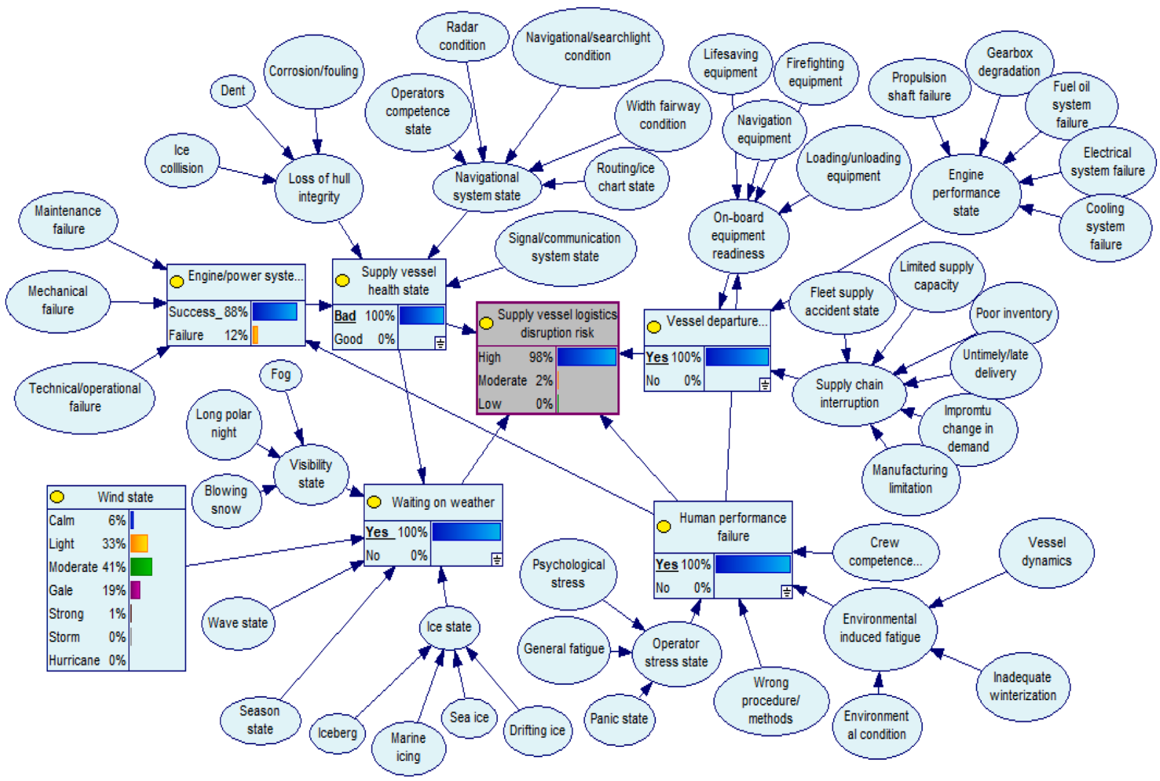

Fig. 17. BN structure for logistics disruption risk prediction considering evidence on core influential factors.

prediction due to operational disruption. The forward learning of the structure shows the likelihood of disruption risk of 0.3314, 0.3085, and 0.3600 for high, moderate, and low-risk states, respectively.

To further explore these influential functions' interactions and their effects on the logistics disruption, evidence is placed on the supply vessel health, vessel departure delay, waiting on weather, and the human performance failure, as shown in Fig. 17. It is observed that there is a shift in the disruption risk by 195% for the high-risk state. By placing evidence, the estimated logistics disruption likelihood was 0.9804, 0.0187 and 0.0009, for the high, moderate, and low-risk states, respectively.

The robust BN structures show the interaction effect among the most critical factors, of disruption risk on offshore supply chain operations. The BN algorithm's merit is its capacity to update the probability of influential parameters given evidence on the main event. Additionally, the interactive effects are propagated across the nodes based on their degree of dependencies. Here, the logistics disruption risk node is set as evidence, and the probability of the influential parameters is updated, as shown in Fig. 18.

The simulation results in Fig. 18 further reveal the degree of impacts of the critical factors, given a high disruption risk during operation. It is observed that at high-risk disruption, the probability of occurrence increases by 21%, 26.8%, 66.6%, and 43.6%, for the supply vessel health, vessel departure delay, waiting on weather, and human performance failure, respectively. The result shows that waiting on weather and human failure states play key roles in the high-risk disruption scenario in harsh arctic offshore operations. In essence, priority should be given to monitor and adequately mitigate these factors to enhance safer offshore support vessel operations in harsh environments.

Furthermore, a diagnostic-based sensitivity analysis is carried out on the most critical influential functions to evaluate their degree of impact on the disruption risk state. Evidence is placed on the assertive state of these factors to predict the likelihood of the associated disruption risk, and the result is shown in Fig. 19. It is observed that by placing evidence on the influential functions, the high-risk disruption likelihood increases by 30.4%, 39.9%, 17.6%, 17.8% the human performance failure, waiting on weather, supply vessel health state and vessel departure delay nodes, respectively. The result provides further insights in the impact of the operating environmental elements (waiting on weather) on the estimated disruption risk in arctic offshore support operations.

The result supports the findings of (Kum and Sahin, 2015; (Rahman et al., 2020b)). This result further illustrates the applicability of the proposed hybrid model.

Upon disruption or operational interruption of the offshore supply vessel operations due to the critical influential factors, the estimated risk likelihood, as presented in Fig. 19, is further developed. The probabilistic risk data is processed using the expectation theory to estimate the incurred cost/economic risk resulting from the vessel's operational disruption. Eqs. (11)-12 are used to model the financial loss/incurred cost due to disruption in the MATLAB environment. A 10^5 simulation runs based on the Monte Carlo algorithm is used to predict the likely economic risk profile for the high, moderate, and low risks for the case study. The Monte Carlo algorithm is a probabilistic tool used for economic risk analysis by sampling the inherently random variables of any given formulation.

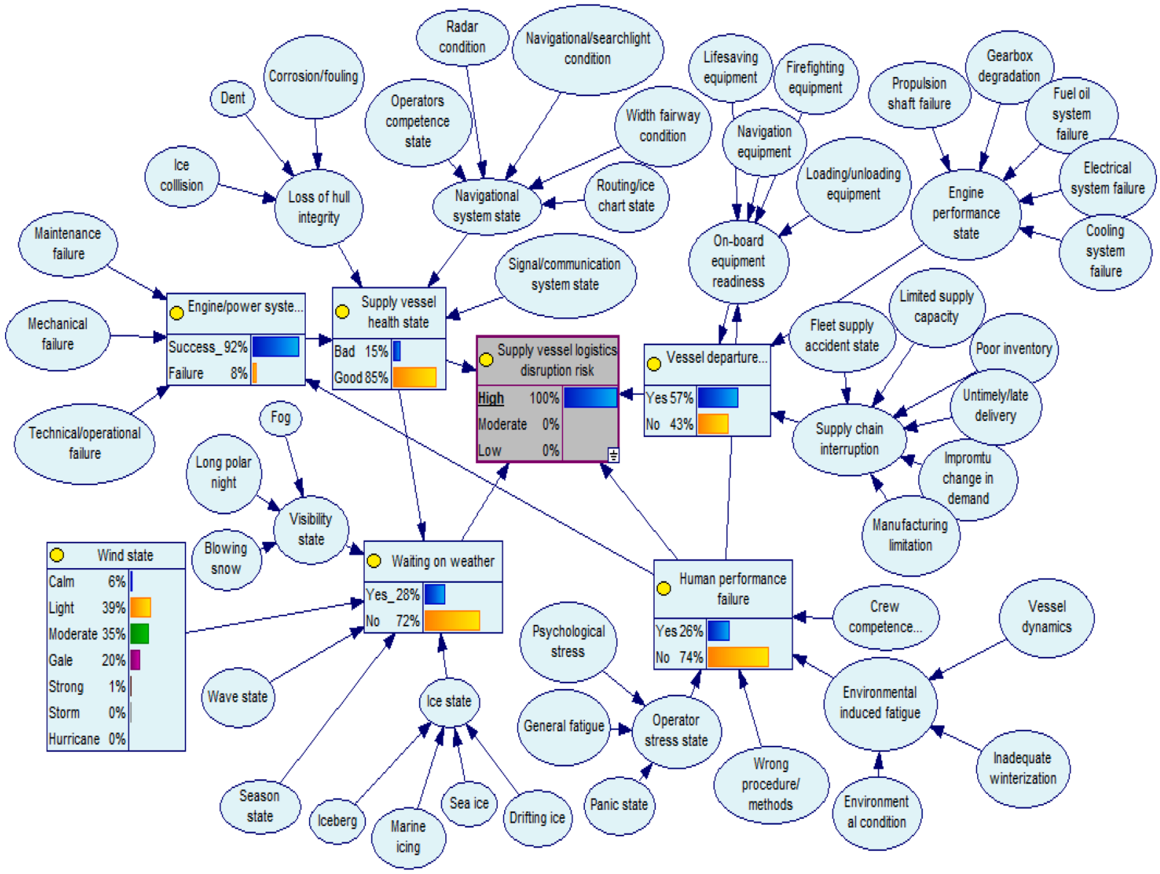

Fig. 18. BN structure for logistics disruption risk prediction considering evidence on disruption risk node.

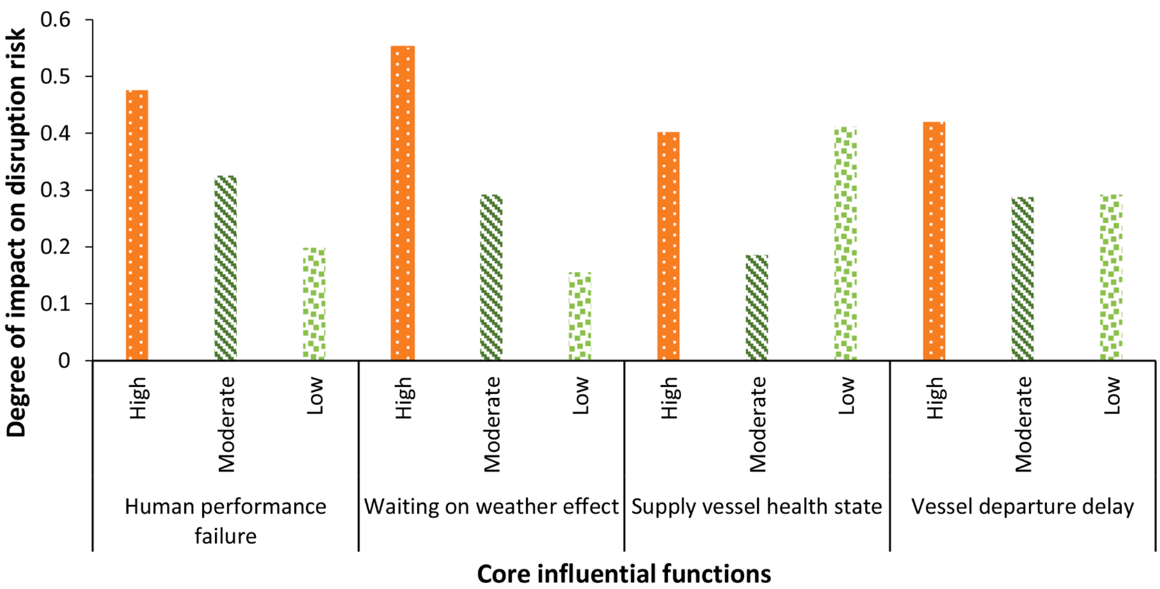

Fig. 19. Degree of disruption risk on influential functions considering hard evidence.

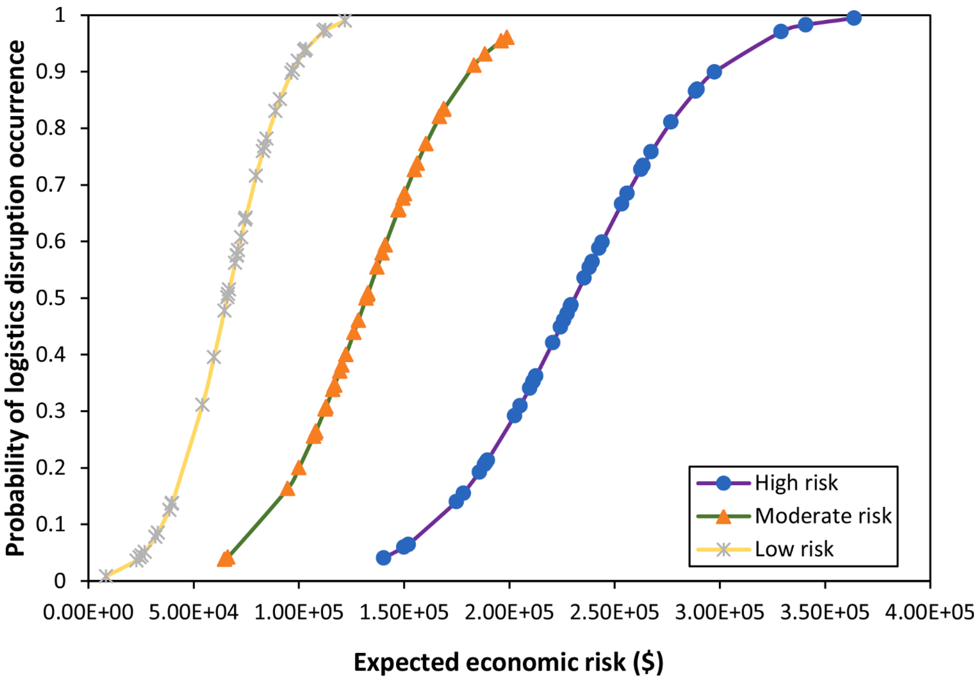

Fig. 20. Expected economic risk/incurred cost due to logistics disruption in offshore support operations.

The simulated aggregate of the incurred cost elements for the studied scenarios is shown in Fig. 20. It depicts the risk profile due to logistics disruption for critical decision-making. The result reflects the cumulative disruption occurrence probability based on the predominant influential functions in harsh offshore logistics operations. It can be inferred that for a known probability of disruption occurrence, given the predefined risk category, the expected economic risk/additional incurred cost can be estimated.

According to Fig. 20, the upper bound expected additional incurred cost due to disruption for quarterly logistics operations can be estimated in terms of the economic risk (value at risk) for each of the core influential functions. The expected economic risk as a result of human performance failure induced logistics disruption is US$2.29E+05 with a variance (σ^2) of 1.06 $\times$ 10^9. The economic risk/additional cost's effect due to weather-induced disruption is US$2.38E+05 with a variance (σ^2) of 3.05 $\times$ 10^9. The estimated additional incurred cost due to the vessel health state and vessel departure delay gives US$2.13E+05 with a variance (σ^2) of 1.03 $\times 10^9$ and US$2.21E+05 with a variance (σ^2) of 1.11 $\times$ 10^9, respectively. The result of the analysis provides risk-based information that will facilitate the forecast of the economic risk/additional incurred cost on the offshore logistics support operations, especially in harsh offshore environments. It is important to note that the variability in the cost parameters and the predicted economic risk may vary depending on the nature of maritime operations and terrain.

The presented hybrid approach provides a proactive stochastic tool for logistics disruption risk estimation for decision-makers and operational managers of offshore support fleet operations. The model's capacity to update the likelihood of the disruption occurrence by placing evidence shows its adaptive potential, which is useful for real-time application in a dynamic ocean environment.

6. Conclusion

The current study demonstrates the development and application of the hybrid PBMP-BN model for logistics disruption risk estimation in harsh offshore environments. The methodology explores the influential functions and their basic elements' dependencies to estimate the disruption risk, rated as high, moderate, and low. The probabilistic data is used to further estimate the additional incurred cost/economic risk based on the cost aggregation technique. The variability in the cost parameters is captured using the Monte Carlo simulation to estimate the economic risk for the given likelihood of occurrence of an event and the effects of the influential functions. The presented model demonstrates the capacity to estimate the degradation probability of the mechanical systems and the disruption risk for the predefined harsh operating environment. The following are key findings drawn from the present study:

- The presented approach is adaptive and serves as a useful dynamic tool for offshore supply vessel logistics disruption risk estimation under real-time conditions.
- The model captures the stochastic degrading potentials of the mechanical systems to predict their failure probability in harsh operating environments.
- The hybrid model propagates the failure characteristics of the engineering systems and the metocean parameters' effect on the disruption occurrence probability during operation.

- The model offers a hybrid structure for expected additional incurred cost/economic risk as a function of the influential parameters. This captures the variability in the cost parameters for the overall additional incurred cost estimation.
- The developed methodology offers dynamic condition monitoring and non-linear dependencies' capacity for decision making.
- The maritime and offshore oil and gas industries could benefit from applying the presented hybrid modeling approach, for stochastic modeling of engineering systems and disruption risk-based forecasting in harsh offshore logistics operations.

The current study illustrates the potential of the presented approach for logistics disruption risk analysis. However, the approach could be further improved by integrating more extensive uncertainty modeling techniques and supply chain optimization methods. The model scope could be extended to include market/discounting risk influencing factors, and the link between risk analysis and decision making could be strengthened by explicitly considering risk minimization as part of the approach and model formulation. This is left for future development.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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