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Dynamic Failure Analysis of Ship Energy Systems Using an Adaptive Machine Learning Formalism

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Abstract: The criticality of shipping operations in global trade requires a comprehensive understanding of its sustainability. This depends on the integrity/performance of the ship structure and vital systems, such as the ship propulsion engine. The current research paper presents the application of an adaptive machine learning formalism, the Bayesian network, for failure assessment of a ship propulsion engine considering nonlinear and nonsequential failure interactions. The model captures critical failure influencing factors and their complex interactions to predict the failure probability of the ship energy system. Sensitivity and uncertainty analysis was carried out to establish the degree of influence of vital failure influencing factors as they affect the ship propulsion engine's reliability and the associated uncertainty in the prior data processing. The model is tested on the propulsion engine of an ocean going vessel to forecast the likelihood of failure based on the logical dependencies among failure causative factors. Two scenarios were analyzed based on canonical probabilistic algorithms, and the results show that upon evidence on the three critical failure modes, the ship propulsion engine failure likelihood increased by 11.8%, 8.2%, and 9.4%, respectively. The model shows an adaptive/dynamic capability to capture new failure information and update the system's failure probability. The proposed approach provides a condition monitoring tool and early warning guide for integrity management of critical ship energy systems.

Keywords: ship propulsion engine, dynamic failure, machine learning formalism, energy systems, Bayesian network

1. Introduction

The tremendous gains from maritime transport have served as a catalyst for civilization and intercontinental trade's lifeline. Though numerous regional and international regulatory bodies have safety conventions in place, major failures/accidents continue to be reported every year for marine vessels (Adumene et al., 2022; Aziz et al., 2019). The ship propulsion power system is a critical system of the ship structure. As such, failure for any reason may result in substantial economic loss or loss of life. Heavy-duty diesel power plants and gas turbine plants are widely used in ship propulsion (Lion et al., 2019). Recently, diesel or diesel hybrid engines have been used in marine propulsion systems to generate mechanical energy from thermal forces. Most vessel types, such as small boats and recreational yachts, use a hybrid energy system for propulsion. The common propulsion engine in the shipping industry is the diesel engine; the diesel engine converts thermal energy to mechanical energy used to exert kinetic force. It is general knowledge that voyages from Port of departure to Port of destination should be completed on time; as such, reducing the potential for failure in the propulsion system is of great importance. Marine diesel engine failure is an operational failure that might result in damage both to the ship and crew members on board (Cicek & Celik, 2013).

The complexity of the marine operations and energy system performance could affect their failure prediction and risk. There exist multidimensional dependency and interdependency among its subsystems during operation. This results in nonlinear and nonsequential failure interactions among subsystems. A better understanding of these failure modes and their interrelationship is crucial for the system's time-dependent failure prediction. Moreover, the system failure's stochastic nature could require a dynamic and robust probabilistic tool that could capture and integrate all causative factors for a reliable failure forecast. The reviewed literature (Arzaghi et al., 2020; Aziz et al., 2019; Carroll et al., 2015; Hatti, 2018; Ossai et al., 2016; Zahraee et al., 2016) has demonstrated the application of probabilistic tools in energy systems reliability and failure analysis. However, they are limited to the dynamic modeling of ship energy systems under complex dependencies.

The Bayesian network (BN) is a machine learning (ML) tool that captures the conditional dependencies among random variables to analyze a given phenomenon. Its inferential reasoning is based on Bayes' theorem. The BN model has shown promise

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for complex system failure modeling under uncertainty (Khakzad et al., 2013). It adopts a logical acyclic directed graph to represent the cause–effect analysis of a given phenomenon. The reviewed literature (Cicek & Celik, 2013; Faturachman et al., 2018; Golub Medvešek et al., 2014), modeled the ship energy reliability based on qualitative and semiquantitative methods. These methods are limited to capturing the interactions among the subsystems. This reveals the weaknesses of the existing model for ship energy system modeling under complex failure modes interactions. Moreover, the interaction and complex dependence among critical failure influential factors in a dynamic ocean environment have not been captured for ship propulsion engine failure. It is essential to adopt an algorithm that could capture the dynamic interactions among failure modes for a reliable system failure prediction under uncertainty.

The current study presents an approach that integrates the failure modes with the ML formalism (the BN) to model the nonlinearity and dependencies among the ship energy systems' failure contributing factors. The model is able to i) apply a data updating algorithm that will update the failure data for real-time risk modeling of ship operations and ii) capture the complex dependencies among failure influential factors for a dynamic failure assessment framework. The energy system's critical failure modes are identified and classified based on their level of importance and functionality. The essential predisposing factors (causative factors) are described based on a logical framework to estimate their probability of occurrence. The formulated frameworks are mapped into the BN to dynamically capture the effects of the subsystem interactions and stochasticity on the ship power plant's failure characteristic. This is intended to capture the variability and uncertainty in the failure initiating parameters and the effects of the dynamic ocean environments. The approach is demonstrated on a ship propulsion engine. It logically represents the various causative factors to capture their interdependency and stochasticity for a robust failure assessment. The likely impact of the subsystems' performance based on a sensitivity analysis was established to identify their vulnerability path for critical decision making.

2. Marine Energy Systems Failure Assessment

The system's reliability defines the performance characteristic of an engineering system for the period of operation. This can be expressed in terms of the failure rate or hazard function for a defined period. Failure of the marine energy system could be catastrophic in extremely harsh ocean environments. Their failure modes could classify the dependency/functionality of the subsystems that characterized the overall system performance.

Several researchers have proposed various failure modes assessment techniques for marine energy systems in the open sources (Banks et al., 2001; Faturachman et al., 2018; Hadiya, 2011; Kang et al., 2017; Lau et al., 2012; Leimeister & Kolios, 2018; Pfaffel et al., 2017). For example, Failure Mode and Effect Analysis (FMEA), HAZOP, FMECA, and What If Analysis are common qualitative approaches widely adopted to analyze the severity, detection, and occurrence of failure events. Recently, Kang et al. (2017) and Pfaffel et al. (2017) proposed the application of FMEA and Correlations-FMEA for marine energy system failure assessment in the ocean environment. The authors identify five fundamental subsystems that define the functionality of the energy system. The critical subsystems could include the structural support system, electrical, turbine generator, transmission, and auxiliary systems. The qualitative approach provides great insight into the system's failure influential factors; however, they are limited to quantitatively predicting the failure likelihood and the complex interactions among basic elements of the plant.

To further capture the logical dependency among the subsystems, a quantitative approach, such as the fault tree analysis (FTA), has been demonstrated for marine system failure assessment (Aziz et al., 2019; Golub Medvešek et al., 2014; Kabir, 2017; Nitonye et al., 2017). The FTA is a method that captures possible failure root causes through a logical relationship. It provides an in-depth structure for failure prediction that results in loss of system integrity (Márquez et al., 2016). Typically, FTA is adapted to predict the top event (failure event) failure probability based on the associated system failure modes and basic events. Furthermore, the basic failure events are not exhaustive; they are dependent on the analyst's knowledge and interaction among the various subsystems (Ta et al., 2017). It is used to deduce the interaction between intermediate events; these interactions could be in the form of a combination of elements with the use of Boolean ("AND/OR") logic gates. Márquez et al. (2016) used the failure modes technique to identify critical failure influential factors and the logical dependencies of marine wind energy systems. The model captures the structural, wear, electrical, and mechanical causative factors as their interplay affects the plant's performance. Ta et al. (2017) recently employed the FTA for the marine propulsion reliability analysis. The intent is to predict the likelihood of propulsion system failure, considering the basic causative factors. The model could predict the failure of the propulsion system upon the availability of the failure characteristics (probability) of the basic events for the period under consideration. However, the Boolean logic gates present a static feature that limits the fault tree's application, especially for a real-life ocean operation/scenarios where the failure characteristic is stochastic and dynamic.

Adumene and Okoro (2020) applied a stochastic Markovian process for marine energy system reliability analysis. The authors captured the stochasticity associated with the failure of the energy systems through a time- and space-dependent framework. The probability of failure over time was predicted, given the failure rate as transition intensity based on the Markovian assumption. Further application of artificial intelligence in ship systems and offshore energy systems analysis has been demonstrated by the researchers (Arzaghi et al., 2020; Carroll et al., 2015; Hatti, 2018; Ossai et al., 2016; Zahraee et al., 2016).

The increasing need for digitization in the marine industry and data mining have created more opportunities to develop advanced data science and ML techniques for the maritime. Recent works that explore the application of ML for marine energy system forecast and other aspects of the maritime operations are detailed in the referenced literature (Cheliotis et al., 2020; Kim et al., 2021; Peng et al., 2020; Planakis et al., 2022; Tay et al., 2021; Uyanık et al., 2020). For instance, Peng et al. (2020) applied the ML formalism to predict ships' energy consumption at Port. The authors adopt 15 modeling features, consisting of inherent ship property and external Port features. The result shows that deadweight tonnage, facilities efficiency, net tonnage, and actual ship weight critically affect the amount of energy consumption of ships at Port. Similarly, Tay et al. (2021) highlighted the pros and cons of applying ML techniques, such as artificial neural networks, hidden Markov model, and Bayesian inference for ship energy efficiency prediction. However, there is no conclusive study on the application of these models for marine energy system failure prediction.

The dynamic and variability in marine energy systems' failure variables require a probabilistic and ML formalism that is dynamic and adaptive, such as the BN. The BN could capture the multidimensional complexity in the energy system configuration to predict its effect on the overall plant performance and failure. Such a benefit is needed to develop a robust failure-based framework for critical ship energy systems during operations. It could also provide a dynamic tool that updates the failure probability upon the availability of new evidence and/or the effect of maintenance on the system performance.

3. Proposed Methodology and Its Application

This section presents the proposed integrated ML algorithm for the failure analysis of marine energy systems. The algorithm is summarized in Figure 1, and the subsequent sections describe the methodological procedure.

3.1. System performance and failure modes

The marine system of study is defined and classified based on its performance/functionality. This is followed by identifying the subsystems and their failure mode. The failure modes assessment tool, such as FMEA, could be adopted to classify the subsystems' level of importance and their role in the entire plant's failure during operation. The interaction among these basic failure influential factors is examined to develop a logical framework for the various failure modes.

3.2 Logical interactive framework for failure modes

The failure modes of marine propulsion engine failure study are presented in Figure 2. Figure 2 shows a schematic of the logical framework of the significant failure modes. It captures the interaction among the identified failure modes for the study scenario. Critical factors that influence the system and their basic predisposing elements are further studied for a robust failure framework for the ship propulsion engine systems. However, a comprehensive logical structure is presented in section 4 for the demonstration of the proposed approach.

3.3. Mapping of logical framework into the ML formalism

Figure 2 shows the developed logical representation of the vital failure modes. This is elaborated and mapped into the BN structure in

Figure 1
Algorithm for dynamic failure assessment methodology

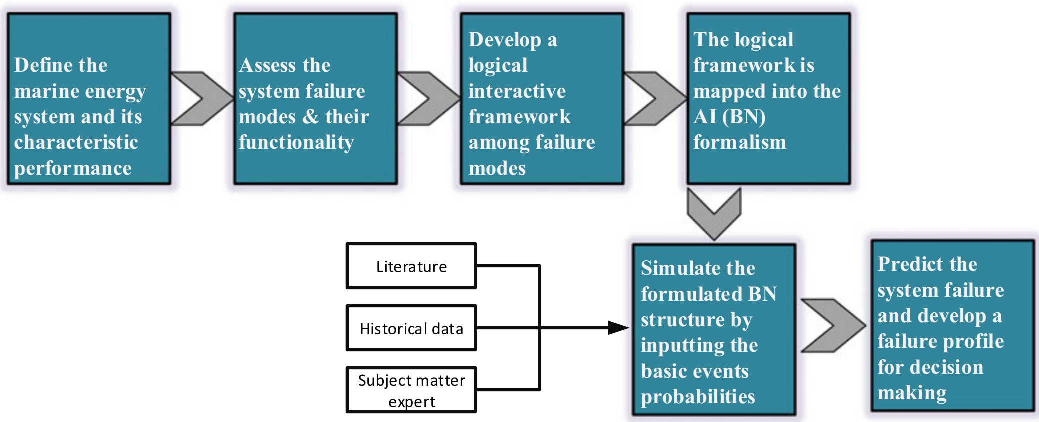
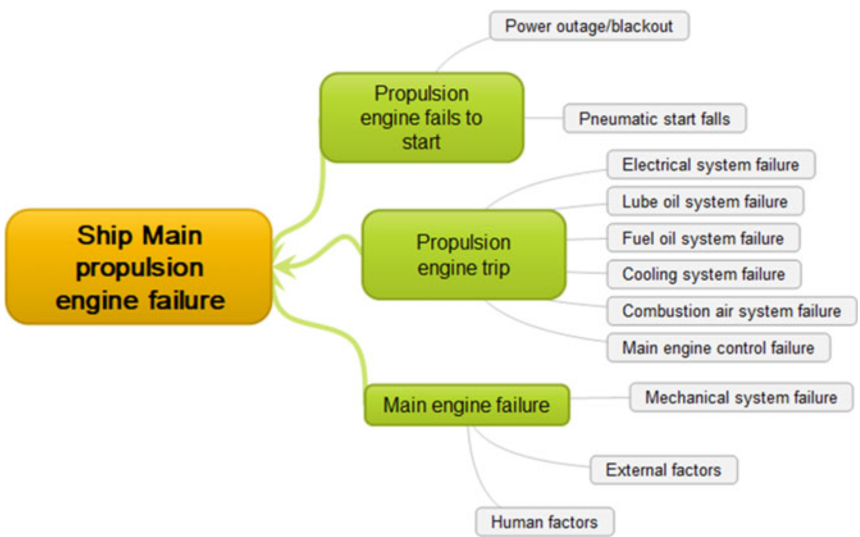


Figure 2
A schematic of the main and intermediate failure modes



section 4. The logical structure used by FTA mapped the basic events, intermediate events, and top events as the root nodes, intermediate nodes, and pivot node of the BN formalism, respectively. More information on the mapping procedures adopted for the research analysis can be found in the referenced literature (Bobbio et al., 2001; Khakzad et al., 2013). For more information on the use of BN formalism, interested readers are referred to the work of Daly et al. (2011).

The BN is a directed probabilistic dependence graph that captures or represents uncertain knowledge in ML (Bobbio et al., 2001; Pearl, 1988). It is applicable for discrete and continuous random variables modeling of a given phenomenon. The BN modeling can identify both the qualitative and quantitative topologies, which in most cases are based on the *d-separation* notion and direct dependence among random variables. Its advantages range from its graphical decoding of conditional independence to joint probability representation among random variables. The BN formalism presents modeling flexibility that accommodates various statistical dependencies and dynamic interdependencies among failure causative factors. The BN formalism shows great merits over the fault tree technique.

For a given set of basic random variables $(X_1, X_2, \ldots\ldots, X_n)$, the joint conditional probability distribution, $P(U)$, gives

$$P(U) = P[X_1, X_2, X_3, \ldots.., X_n] = \prod_{i=1}^{n} P[(X_i|Parent(X_i))] \quad (1)$$

where $P(U)$ is the joint probability distribution, and $Parent(X_i)$ is the parent of the set of random variables, X_i.

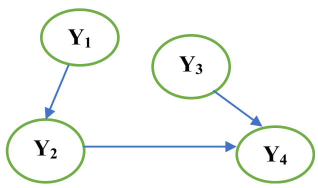
The BN consists of various algorithms for inference and computing of the posterior probability distribution on a set of query variables designated as Q, for a given evidence called E (i.e., $P(Q|E)$). Figure 3 represents a conventional BN structure for random variables Y_1, Y_2, Y_3, Y_4. Also, the BN formalism can update the probabilities for new information or change in the characteristic variables. For example, given an observed variable Y_3 to be in state e, the joint probability distribution can be updated based on the Bayes' theorem, as shown in equation (2).

$$P(Y_1, Y_2, Y_4|e) = \frac{P(Y_1, Y_2, Y_4|e)}{\sum_{Y_1,Y_2,Y_4} P(Y_1, Y_2, Y_4, e)} \quad (2)$$

3.4. Structural and parametric learning of BN structure for decision making

Structural learning methods of the BN from the dataset have been demonstrated in the literature. The two common learning methods include the score-based and constraint-based approaches. These methods considered learning the dataset based on the conditional independence relationship among the data points and

Figure 3
Schematic of a conventional BN structure



maximizing the likelihood of the model (Beretta et al., 2017; Chickering, 2002; Daly et al., 2011). In the constraint-based approach, the Incremental Association Markov Blanket (IAMB) algorithm and PC algorithm have proven effective in learning the BN model, while the score-based approach adopted the maximum likelihood estimation algorithm. For instance, the learning process based on the likelihood maximizer $\mathcal{L}$ of a set of failure data D for a given model $\mathbb{G}$ can be expressed by equation (3) (Beretta et al., 2017).

$$\mathcal{LL}(\mathbb{G}; \mathbb{D}) = \prod_{d \epsilon D} P(d|\mathbb{G}) \quad (3)$$

The common algorithm for the score-based approach is the Bayesian information criteria (BIC). The algorithm adopts the log-likelihood and regularization terms to define the model structure from the failure/observed dataset, D. It can be expressed by equation (4).

$$BIC\ (\mathbb{G}; \mathbb{D}) = \mathcal{LL}(\mathbb{G}; \mathbb{D}) - \frac{\log m}{2} dim(\mathbb{G}) \quad (4)$$

where D denotes the dataset, m indicates the number of samples, and $dim(\mathbb{G})$ is the number of parameters in the BN model.

The formulated ML formalism is learned based on the score-based approach for the basic events (root nodes) probability of occurrence and the conditional probabilities that describe the dependencies. This is quantified as a conditional probability table (CPT). The root nodes' probabilities are numerical values from historical failure data, expert opinions, and literature. This defined the initial state of the systems and the belief about their performance. For this analysis, n-array variables are adopted to depict the component behavior in a real-life case. This captures the possible presence of multifailure modes and their probabilities between 0 and 1. The CPT is defined based on the Noisy gates' principles for the likely multifailure. When changes occur due to the system's environmental dynamics and stochasticity, the BN can be updated based on the new information. For the parametric learning of the BN structure, the nodes are categorized into success and failure. The probability of failure of the pivot node (ship propulsion engine failure) can be simulated for multiple scenarios for the period under consideration.

Furthermore, the sensitivity analysis examines the degree of influence of the basic failure influencing factors on the pivot node. The essence is to identify the critical input parameters that significantly impact the energy system's failure profile and provide safety barriers/measures. It also propagates the uncertainty for the random input dataset to the output of the model. The variance reduction technique is adopted for the sensitivity analysis of the BN model's output for this research. The technique is based on the expected reduction in the variance of the characterized value Q given the evidence R. It is mathematically represented by equation (5) (Pearl, 1988; Shabarchin & Tesfamariam, 2016).

$$V(q|r) = \sum_{q} P(q|r) [X_q - E(Q|r)]^2 \quad (5)$$

where q is the state of the query node Q, r is the state of varying node R, $P(q|r)$ is the conditional probability of q when node R is given to be in state r, X_q is the numerical value corresponding to state q, and $E(Q|r)$ is the expected real value of Q due to a finding of the state r in node R.

The quantification and model learning of the failure data present some uncertainty due to randomness and errors. To evaluate the associated error and uncertainty in the dataset due to the randomness for the study phenomenon, equations (6) and (7) are adopted

$$SE_{\bar{x}} = \frac{S}{\sqrt{n}} \tag{6}$$

$$U_{\bar{D}} = \pm \frac{t * S}{\sqrt{n}} \tag{7}$$

where S is the deviation of the mean, n is the total number of elements, $SE_{\bar{x}}$ is the standard error of the sample mean, $U_{\bar{D}}$ is the uncertainty randomness in the dataset, and t is the t-test statistic at 95% confidence level.

For the current study, multiple scenarios are developed to demonstrate different failure profiles and vulnerability paths under various operational decision-making scenarios. All BN structures in this study are modeled in the GeNIe™ software environment.

3.5. Methodology application

The proposed approach is demonstrated with a case study of ship propulsion engine failure (Aziz et al., 2019; Kum & Sahin, 2015; Lion et al., 2019). This provides validation and demonstrates the applicability of the ML formalism in ship energy system failure analysis. As presented in the referenced literature (Aziz et al., 2019), the logical framework is used to apply ML formalism in this research. The probabilistic failure dataset presented by Kum and Sahin (2015) was used for the proposed model's structural learning (training), while Table 1 shows the prior probabilities dataset of the principal events for the model test and validation (Aziz et al., 2019).

The proposed approach's computational procedure is applied to the case study based on the system's data, as shown in Table 1. The results outcome is shown in Section 4.

4. Results and Discussion

The current research objective is to demonstrate the application of the ML formalism (the BN), for failure prediction of the ship propulsion energy system under uncertainty. This is shown by i) utilizing the data updating algorithm in the ML formalism to update the failure data for real-time failure modeling in ship operations and ii) capturing the complex dependencies among failure influential factors for dynamic failure assessment. The BN captures the various failure influencing factors dynamically and predicts their dependencies' effect on the ship power plant's probability of failure. The critical failure modes were represented and evaluated based on the prior probabilities, as shown in section 3. The ML formalism captures both the parametric and structural learning of the parametric interactions among crucial failure influential parameters of the ship energy system. The parameter learning result of the BN structure is shown in Figure 4. The result shows that for the given failure data, as indicated in Table 1, the ship propulsion engine failure's likelihood is 0.9999 based on the Boolean logic (0 1]. This is adopted for the CPT formation based on a deterministic logical-OR gate analysis. It implies that for a state of affirmation on the subsystems' failure states, the learning of the structure confirmed that the ship propulsion engine would fail. This is due to the logical interrelationship of the main engine failure, propulsion trip failure, and failure to start modes. The interdependency demonstrated in parametric learning shows that one failure mode's occurrence causes the ship engine's failure. However, in many real-case scenarios, there exist different failure states or latent failure/faults that may influence the CPT formation based on the belief of the degree of interactions/dependency among failure causative factors. To capture this scenario, the canonical noisy-OR gate is introduced, as shown in Figure 5.

Figure 5 shows the result of the ship propulsion engine failure profile under noisy-OR configuration. The essence is to capture scenarios when latent failure/faults in the system affects the system's functionality but does not result in total failure. This represents cases where there exists a nonsequential failure process as well (Adedigba et al., 2016). The noisy-OR model demonstrates the ability to consider a reconfigured system performance in the presence of latent failure/faults. As shown in Figure 5, the likelihood of failure for the propulsion engine fails start node in comparison with the result in Figure 4 increases by 55.6% under the noisy-OR gate configuration. While that of the main engine failure and the propulsion engine trip failure nodes probabilities decreases by 89.9% and 20%, respectively.

To further analyze the failure state's effect of the failure modes on the ship propulsion engine failure likelihood, the evidence is placed on the "Yes" state for the main engine node, propulsion engine trip node, and propulsion engine fail to start node. Learning the structure under evidence shows that the ship propulsion engine failure probability increases by 11.8%, 8.2%, and 9.4%, respectively. The work demonstrates the BN's adaptive nature to capture any change(s) in belief or information on the state of failure of the influential critical factors to predict the pivot node's performance state. This reflects the real case scenarios where common cause failure and latent faults are predominant.

Sensitivity analysis examines the influence of the most critical failure influential parameters on the pivot node failure state. In this case, the nodes' failure data variance is evaluated based on the method presented in Shabarchin & Tesfamariam (2016). The sensitivity analysis result is shown in Figure 6.

The normalized percentage of the ship propulsion engine failure parameters, as shown in Figure 6, indicates that the pneumatic start system failures show more significant effects. This represents over 15% influence on the frequency of failure of the ship propulsion plant. This is followed by the air system failure that results in a lack of starting air for the demonstrated case study. The drive (shaft) line functionality is crucial in the sustainable operation of the power plant. Its frequency of failure accounted for 4.7% of the total system failure. The degree of inference of the other parameters can be deduced from Figure 6. Understanding the effect of the variations in the vital basic elements on ship propulsion engine performance will aid parametric integrity management, especially in harsh ocean conditions, where environmental constraints pose additional load effect on the ship propulsion. The energy need in harsh weather ship operation and the interdependencies among the critical subcomponents could create degradation and fatigue-related failure of the system. This provides an initial validation to the model application.

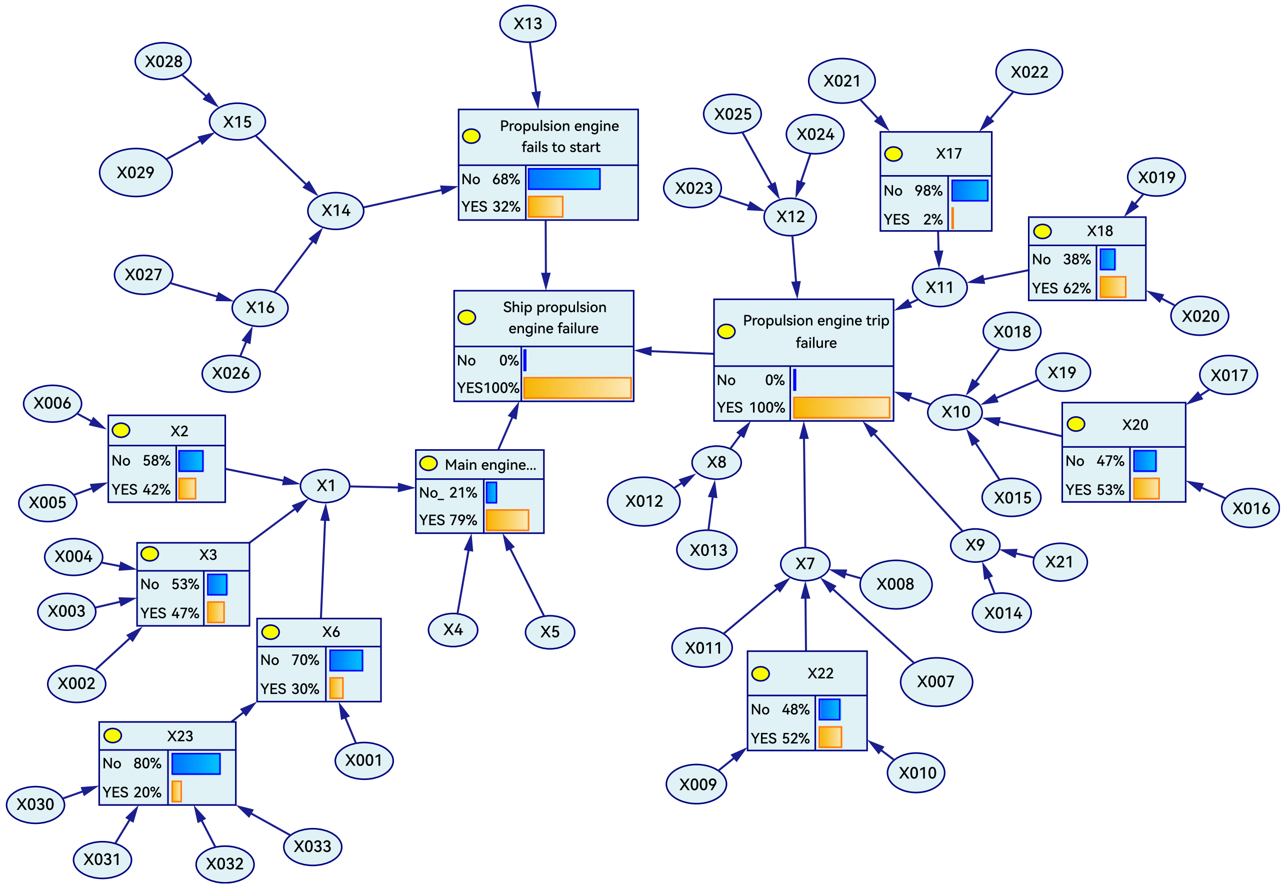
The modeling of the uncertainty in the dataset and the proposed models' epistemic uncertainty is based on the test statistic. The epistemic is inherent in the assigned/learned CPT of the BN structure and is propagated to the output. The analysis result

Table 1
Principal events of ship propulsion engine failure

Main event	Main intermediate events	Codes	Subintermediate events	Codes	Basic events	Codes	Basic events probability
Ship propulsion Engine failure	Main engine (M/E) failure	XA	Mechanical failure	X1	Scaled or worn valves	X001	0.133
	Propulsion engine trip	XB	Drive malfunction	X2	Cylinder wear	X002	0.128
	Propulsion engine fails to start	XC	Mechanical seizure	X3	Bearing overheat	X003	0.075
			Human failures	X4	Loss of lubrication	X004	0.349
			External failures	X5	Stern tube and gearbox fails	X005	0.409
			Main engine compressor	X6	Coupling failure	X006	0.017
			Main engine control system	X7	ECU/hydraulics	X007	0.173
			Combustion air system failure	X8	FIVA and speed governor	X008	0.249
			Cooling system failure	X9	Air compressor failure	X009	0.393
			Fuel oil system failure	X10	Control air supply failure	X010	0.209
			Lube oil system failure	X11	CCU/ACU control	X011	0.370
			Electrical system failure	X12	M/E blower fail	X012	0.487
			Power outage/blackout	X13	M/E Turbocharging fail	X013	0.133
			Pneumatic start system failures	X14	Scaled cooler	X014	0.982
			Lack of start air	X15	Fuel injector failure	X015	0.474
			Start-up hydraulic pressure	X16	Poor quality of fuel	X016	0.400
			Low flow of lube oil	X17	Fuel filter block	X017	0.221
			Lube oil pressure drop	X18	F/O booster fails	X018	0.160
			Fuel oil supply	X19	L/O leakage	X019	0.002
			Poor fuel oil quality	X20	L/O purifier fails	X020	0.623
			Low flow of cooling water	X21	L/O pump fails	X021	0.077
			Pneumatic controller failure	X22	Pneumatic L/O supply fails	X022	0.213
			Cylinder mechanics failure	X23	Short circuit	X023	0.010
					M/E sensor failures	X024	0.133
					Trip signal malfunction	X025	0.503
					Service air compressor failure	X026	0.632
					Start-up hydraulics	X027	0.865
					Bottled air pressure low	X028	0.057
					Compressor fails	X029	0.300
					Cracking of cylinder block	X030	0.020
					Deadlocking of piston ring	X031	0.050
					Breakage of piston	X032	0.030
					cracking of liner	X033	0.112

M/E, main engine; CCU, cylinder control unit; ECU, engine control unit; ACU, actuator control unit; F/O, fuel oil; L/O, lube oil.

Figure 4
Result of the parametric learning of the BN structure



indicates that the standard error associated with the deviation from the mean is ±0.0418. However, the deviation effects for each data point may show some diversity in the errors as predicted. This is crucial considering the failure data learning/partitioning process for prior probability estimation of the various ship engine subsystems. The uncertainty due to dataset randomness at a 95% confidence level is ±0.0855. The essence is to understand the characteristic nature of the input data (prior probability) and the assigned/learned CPT of the basic influential factors on the model outcome. Upon the prediction of the uncertainty, it is propagated into the predicted output. This process of uncertainty propagation or casual error propagation is crucial in the model validity. This is an important measure of the proposed model's performance in failure analysis. The proposed method offers better performance in ship energy system modeling in comparison with the works of Cicek & Celik (2013), Faturachman et al. (2018), and Golub Medvešek et al. (2014). The ability to capture multidimensional dependencies enhances the model application in complex system analysis.

The proposed approach has shown the capacity to capture influential critical factors and the various failure modes for ship propulsion engine failure analysis. The dynamic and updating strength of the ML formalism is of practical importance for ship operations in unstable ocean environments. The approach benefits the maritime industry as a tool for condition monitoring and integrity management of critical marine energy systems against total failure.

5. Conclusions

The current study has shown the application of an adaptive ML formalism, the BN, for failure analysis of a ship propulsion energy system. The approach explores the vital influencing factors and their criticality for the overall plant failure prediction. The model captures the effects of dependencies and interdependencies among failure influential factors and predicts the ship energy system's dynamic state. It is observed that the pneumatic start system, starting air system, and drive system significantly affect the frequency of failure of the plant. The model captures the uncertainty in the dataset and propagates through the structural learning process for a reliable output prediction. This provides validation to the model application in ship energy system modeling. The following are vital findings of the current research study:

- The applicable model provides a useful tool for dynamic failure analysis of ship energy systems.
- The approach captures the nonlinear and nonsequential interactions among key failure influential factors for ship energy

Figure 5
Parameter learning of the BN structure under noisy-OR gate configuration

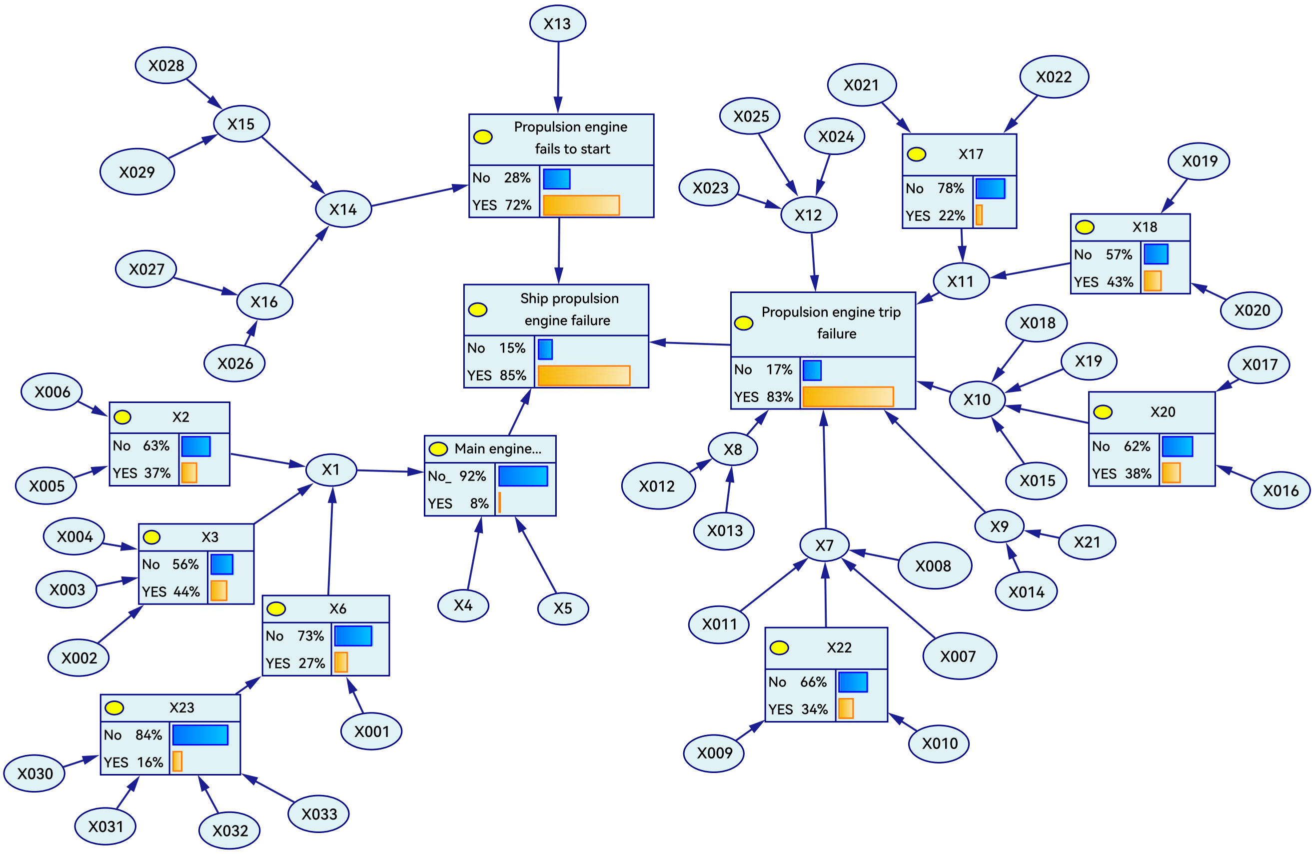
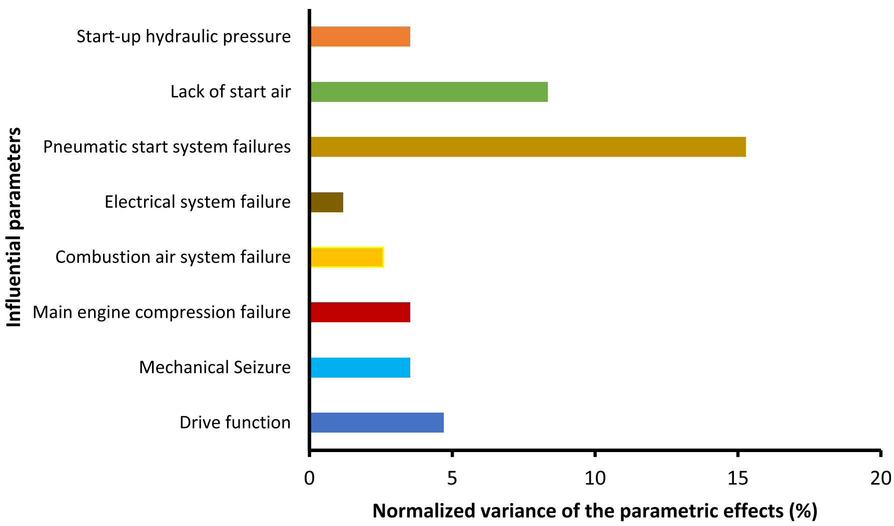


Figure 6
Sensitively analysis of influential parameters on the pivot node



system failure prediction and demonstrates it updating/adapting capacity upon the availability of new failure information.

- The approach could capture the effect of critical systems' soft failure and their interaction on the overall plant failure under diverse belief systems based on the OR-gate and the noisy-OR gate configurations.
- That the model could propagate the casual error and uncertainty in the prior probability estimation of the basic events to the top event failure prediction.
- The approach captures the effect of the variation in variance through the sensitivity analysis to predict the parametric degree of influence on the overall failure prediction.

- The maritime industry stands to benefit from the approach's capability to monitor and manage critical energy systems during marine operations. This provides a guide/early warning against total failure of the critical ship systems.

The application of the adaptive/dynamic model confirms its advantages in failure assessment of ship energy systems under uncertainty. Nevertheless, the proposed approach could be improved in future study with the inclusion of safety barriers modeling and the integration of loss function technique for economic risks prediction in shipping/marine operations.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

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