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Development of a technical condition assessment algorithm for complex systems based on probabilistic failure estimation

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Abstract. This study proposed an integrated algorithm for assessing the technical condition of ship power plants, combining case-based reasoning (CBR), Bayesian networks, Markov processes, and cognitive simulation modelling. The algorithm was designed to enhance the accuracy and adaptability of diagnostics under conditions of uncertainty, limited data, and dynamic operational environments. The diagnostic process followed a multi-stage architecture that included the retrieval of historical failure cases, probabilistic correction based on interdependencies among components, modelling of component degradation over time, and adaptive scenario analysis. Each component of the algorithm plays a distinct role: CBR provides analogies to previously observed failures; Bayesian networks quantify probabilistic links between interrelated faults; Markov chains model the temporal degradation of equipment and estimate transition probabilities between operational states; and cognitive modelling allows the generation and testing of rare or cascading failure scenarios under variable conditions. The integration of these elements ensures that the algorithm dynamically updates failure probabilities and adapts to changing operational data. Simulation results demonstrated several improvements: the average prediction error for remaining useful life of components was reduced from 9% to 5.7%; the accuracy in identifying rare and cascading failures increased by 18% due to the use of cognitive modelling; and Bayesian correction reduced false positive diagnoses by 7.2% compared to baseline CBR systems. Overall, the predicted failure probability for 25,000 hours of operation was reduced from 83% (Bayesian-only model) to 68% with full model integration. The practical significance of the proposed algorithm lies in its ability to improve predictive maintenance planning, reduce equipment downtime, and increase the operational reliability of complex marine engineering systems. The modular architecture also enables the adaptation of the algorithm to various types of industrial technical systems

Keywords: predictive maintenance; probabilistic modelling; cognitive simulation; integration of diagnostic methods; adaptive technical solutions; expert systems; intelligent monitoring

Introduction

Failures in the operation of complex technical systems (CTS) remain one of the leading causes of man-made accidents in sectors such as transport, aviation, and power engineering. Maritime transport is no exception. Statistical analysis shows that despite ongoing efforts to improve navigation safety, the number of ship-related incidents remains significantly high. A detailed examination of these accidents indicates that technical failures of ship power systems are among the primary contributing factors, highlighting the need for more advanced diagnostic and predictive maintenance tools (Vychuzhanin & Vychuzhanin, 2025).Technical condition assessment of a ship power plants (SPP) is a complex task that requires a comprehensive approach, taking into account both historical failure

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data and probabilistic forecasting of their development (ISO/IEC 31010:2019, 2019).

Recent research in the field of technical diagnostics and failure prediction for SPPs demonstrates the effectiveness of integrating various methods, such as technical condition (TC), Bayesian networks, Markov processes, and machine learning techniques. In the review by I. Poljak *et al*. (2022), it is emphasised that the transition from corrective to condition-based maintenance can significantly reduce costs and increase the reliability of ship power systems. They highlight the importance of integrating TC with intelligent diagnostic systems. However, the implementation of TC is often limited by the lack of adaptive models capable of considering complex failure interdependencies among components. T. Ademujimi & V. Prabhu (2021) proposed a "fusion-learning" method for constructing Bayesian networks, combining quantitative and qualitative data. Nevertheless, their model is primarily focused on diagnostics based on known scenarios, with limited ability to predict new or rare failures. P.G. Morato *et al*. (2022) presented an integration of dynamic Bayesian networks with Markov decision processes for optimising maintenance strategies. However, their model is mainly oriented toward individual components and requires a significant amount of reliable data for effective operation. In their work, H. Nikpour & A. Aamodt (2021) proposed the BNCreek system, combining CBR methods and Bayesian networks for diagnostics under uncertainty. Although the BNCreek approach demonstrates high efficiency in several industries, it insufficiently considers the temporal dynamics of degradation processes. A.N. Abbas *et al*. (2022) integrated hidden Markov models and deep learning methods for predictive maintenance. Despite high accuracy, their architecture requires large amounts of training data and is complex to interpret for practical implementations in the maritime sector. The potential of graph neural networks (GNNs) for diagnosing complex interconnected systems was noted in the article by Z. Zhang & L. Wu (2024) However, the application of GNNs to ship power systems demands substantial computational resources and careful graph structure design, complicating their use in real-world conditions. J. Wang *et al*. (2019) applied Bayesian networks for fault isolation in diesel engine fuel injection systems. Their approach is effective for fault localisation but is less suitable for long-term prediction of equipment remaining useful life. Given the susceptibility of marine pumps and rotating components to mechanical degradation under cyclic stress, approaches similar to those applied to high-load torsion shafts (Krakhmalyov *et al*., 2024) are applicable for defining degradation scenarios.

The conducted literature analysis shows that existing methods are either limited in their ability to dynamically forecast degradation, require large datasets, or insufficiently consider complex failure interdependencies among ship power system subsystems. The aim of this study was to develop a technical condition assessment algorithm for SPP based on the integration of CBR methods, Bayesian networks, Markov processes, and cognitive simulation modelling, which will ensure: dynamic model updates as new data becomes available; accounting for probabilistic dependencies between equipment components; forecasting equipment degradation over time; adapting technical condition forecasts to real operational conditions.

Materials and Methods

The technical condition assessment in this study targeted critical components within the SPP, such as circulation pumps, lubrication systems, cooling units, and thermal exchangers. These components were selected due to their high failure frequency and significant impact on overall system performance (Park & Kim, 2024). The developed algorithm is applicable to other SPP subsystems as well, but validation was carried out using models of these key components based on real-world failure statistics. The development of the algorithm for assessing the technical condition of SPPs was based on a step-by-step methodology that integrates empirical failure data, probabilistic modelling, and simulation-based scenario generation. The objective was to model the degradation and failure behaviour of key components within SPPs, such as pumps, turbines, cooling systems, and fuel supply units under realistic operational conditions and to evaluate the algorithm's predictive performance in those contexts. The research utilised both real-world historical data and synthetic simulation data. Historical failure records were sourced from the OREDA – offshore reliability data handbook (OREDA, 2015) database, which contains statistically verified reliability and maintenance data for offshore and maritime systems. The selected dataset included failure modes, mean time to failure, operating time, failure mechanisms, and contextual parameters for over 450 failure events related to components typically found in SPPs. These data provided the foundation for constructing representative failure patterns and probability distributions. In addition to historical failures, a dataset of operational parameters was used to represent typical functioning modes of SPPs. These parameters: temperature (°C); pressure (bar); vibration levels (mm/s); fuel consumption (kg/h). The synthesised based on manufacturer specifications and OREDA-derived profiles. Since access to continuous monitoring data from actual ships was limited, simulation models were calibrated to reflect known operating ranges, failure onset thresholds, and degradation trends observed in real systems. The algorithm modelled the degradation processes of specific components of SPPs, tracking their transitions across operational (0), degraded (1), pre-failure (2), and failure (3) states. The time-dependent evolution of state probabilities was described using a continuous-time Markov process. The probability of component *i* being in state *S* at time *t* is governed by:

$$\frac{dP_i(S,t)}{dt} = \sum_{j \neq i} \lambda_{ji}(S) \cdot P_j(S,t) - \sum_{j \neq i} \lambda_{ij}(S) \cdot P_i(S,t), \quad (1)$$

where S is the discrete state of the unit (0, 1, 2, 3 – where 0 indicates operational, 1 indicates degradation, 2 indicates pre-failure, and 3 indicates failure); $P_i(S, t)$ is the probability of unit i being in state S at time t; λ_{ij} is the transition rate of the unit from state i to state j; λ_{ji} is the reverse transition rate of the unit from state j to state i. The remaining useful life (RUL) of a component is estimated by integrating the probability that it remains in an operational or degraded state:

$$R_i(t) = \int_t^{\infty} P(S_i = 0,1)\, dt, \qquad (2)$$

where $P(S_i = 0,1)$ is the probability that the component remains operational at time t.

This reflects the expected duration for which the component will continue functioning before entering a pre-failure or failure state. In addition to time-dependent degradation, the model accounts for probabilistic dependencies between components. These dependencies are captured using a Bayesian network. If the failure of unit j influences the probability of failure of unit i, this is represented as:

$$P(U_i \mid U_j) = \alpha_{ij} \cdot P(U_j), \qquad (3)$$

where α_{ij} is the influence coefficient representing the effect of the failure of unit j on unit i.

This formulation allows cascading effects to be modelled and incorporated into failure forecasting. A discrete approximation of RUL can also be used for practical implementation:

$$R_i = \sum_{t=0}^{T} P(S_i = 0,1). \qquad (4)$$

This expression calculates the cumulative probability that the unit remains operational or degraded up to a specified time horizon T, supporting engineering estimations and decision-making. The state transitions used in the Markov model are summarised in the transition matrix shown in the Table 1.

Table 1. State transition matrix for SPP units

State	Operational (0)	Degradation (1)	Pre-Failure (2)	Failure (3)
Operational (0)		λ_0		
Degradation (1)			λ_1	
Pre-failure (2)				λ_2
Failure (3)				

Source: created by the authors

To address complex or rare operational scenarios not fully represented in historical data, cognitive simulation modelling was applied. Synthetic degradation scenarios were generated under varying conditions, including overload, delayed maintenance, and environmental stress. These enriched the training space for the model and improved its ability to forecast low-probability, high-impact failures. CBR was used to retrieve similar failure cases from the OREDA-based database. Components with abnormal operating parameters were compared against known precedents using a similarity metric. Bayesian reasoning was then used to refine the initial diagnostic hypothesis by accounting for component interdependencies. Combined with the time-aware Markov framework and cognitive simulations, this formed a unified diagnostic process. Table 2 summarises the core diagnostic methods and their respective functional roles within the system.

Table 2. Distribution of diagnostic methods and their functional purposes

Diagnostic method	Functional purpose
CBR	Search for similar failures in the database, analysis of fault causes
Bayesian networks	Assessment of probabilistic dependencies between components
Markov processes	Prediction of failure evolution over time
Simulation modelling	Reproduction of failure scenarios, evaluation of parameter influence

Source: created by the authors

All modelling and simulation tasks were implemented in Python environments. Each component was simulated over an operational period of up to 25,000 hours. The degradation behaviour was adapted to the characteristics of different component types, and model parameters were iteratively calibrated based on the statistical distributions provided by the OREDA database. The simulations incorporated three typical operational regimes: nominal, moderate-stress, and high-stress, to account for variability in real-world usage. The integrated model combines outputs from CBR, Bayesian inference, Markov-based degradation forecasting, and cognitive simulation. Its performance was evaluated based on RUL prediction accuracy, rare failure detection, and false positive rate. Benchmark testing against a standalone CBR model confirmed that the integration of probabilistic and simulation methods significantly improves diagnostic reliability and robustness.

The diagnostic and forecasting algorithm includes the following stages: (1) data collection based on real and simulated sources; (2) case retrieval using CBR; (3) estimation of conditional state probabilities via Bayesian networks; (4) degradation modelling using a Markov transition framework; (5) dynamic model correction based on incoming operational data; (6) generation of predictive reports and decision support materials, such as failure probability graphs and RUL estimates. This hybrid methodology provided a mathematically rigorous yet practical basis for assessing the condition of SPP components. By integrating empirical reliability data, probabilistic reasoning, and simulation-driven scenario analysis, the proposed algorithm enables adaptive diagnostics and failure forecasting suitable for real-world marine applications.

Results and Discussion

To evaluate the dynamic behaviour of SPP components and the effectiveness of the proposed diagnostic model, a time-based simulation was conducted using the developed Markov framework. The simulation estimates the probabilities of a component being in one of four technical states – operational, degraded, pre-failure, or failure over an extended period of use. The input parameters were derived from statistical failure data in the OREDA database, supplemented with expert assumptions regarding component aging and degradation trends. The modelled components included marine pumps and heat exchangers, which are known for their criticality and susceptibility to gradual wear. Using the transition matrix, the probabilities of the units being in various technical states at specific time intervals were calculated based on the Markov model. Table 3 shows the results of these calculations over a 25,000-hour operating period, corresponding to the typical service life of such equipment.

Table 3. Calculation of technical state probabilities (Markov model) based on simulation results

Time (hours)	P(Operational)	P(Degradation)	P(Pre-Failure)	P(Failure)
0	1.00	0.00	0.00	0.00
5,000	0.85	0.10	0.04	0.01
10,000	0.60	0.25	0.10	0.05
15,000	0.40	0.30	0.18	0.12
20,000	0.25	0.28	0.25	0.22
25,000	0.10	0.22	0.30	0.38

Source: created by the authors

The simulation results demonstrate a clear trend of gradual degradation and increased risk of failure as operating time progresses. During the initial 5,000 hours, most components remain in operational condition, with failure probabilities not exceeding 1%. However, between 10,000 and 20,000 hours, the likelihood of degraded and pre-failure states increases markedly, reflecting the onset of aging-related deterioration. By 25,000 hours, the probability of failure reaches 38%, and the probability of being in pre-failure or failure states combined exceeds 68%. These results are consistent with empirical reliability patterns reported in OREDA and confirm that the model adequately reflects long-term degradation behaviour. The data used in the simulation were generated based on Markov transition rates calibrated using historical failure statistics for maritime mechanical components, particularly pump and cooling systems. Figure 1 illustrates the probabilistic transitions between the states of the SPP and enables the forecasting of degradation and cascading failures. These transitions are modelled as a time-dependent Markov process, where each state represents a specific level of component degradation. The dynamic evolution of state probabilities facilitates the early detection of critical degradation phases and supports timely maintenance interventions.

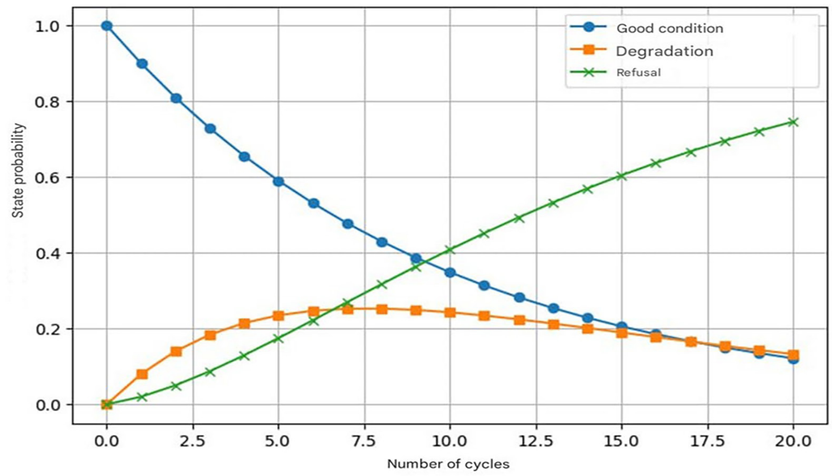

Figure 1. Forecast of SPP failure probabilities over time (Markov model)
Source: created by the authors

Figure 1 shows the dynamics of changes in the probabilities of three states: operational state (blue line, dots) – the probability that the SPP remains fully functional; degradation (orange line, squares) – the probability of the SPP being in an intermediate state between operational and failed; failure (green line, crosses) – the probability of complete system failure. Key observations. Decrease in operational probability: initially, the probability of the operational state is 1.0 (100%), but it decreases exponentially over time as the number of cycles increases. This reflects the natural process of wear and damage accumulation in the SPP. Increase in failure probability: the failure probability (green line) starts at zero but rises over time and becomes dominant after approximately 12-15 cycles. This corresponds to the probabilistic wear model, where the likelihood of failure becomes higher in the later stages of system operation. Peak degradation probability: the probability of being in the degraded state (orange line) initially increases, reaching a peak around 7-8 cycles, and then decreases. This indicates that the system initially undergoes gradual degradation before most failures transition into complete malfunction. The graph confirms the expected pattern of gradual deterioration of the SPP condition. To provide a concise overview of the relative effectiveness of the different diagnostic models, Table 4 summarises the quantitative performance indicators for the baseline CBR model and the proposed integrated algorithm. The integrated model includes Bayesian probabilistic correction, Markov-based degradation forecasting, and cognitive simulation to enhance diagnostic depth and reliability.

Table 4. Comparative performance of diagnostic models

Metric	CBR model	Integrated model	Improvement
Accuracy of failure prediction	76%	90%	+14%
Detection accuracy for rare/cascading failures	62%	80%	+18%
Average error in RUL estimation	9.0%	5.7%	–3.3%
False positive rate	12.4%	5.2%	–7.2%

Source: created by the authors based on simulation results based on degradation models calibrated by OREDA

These results confirm the significant advantages of the integrated model. It outperforms the standalone CBR model across all key performance metrics. The improved accuracy in failure prediction and remaining useful life estimation demonstrates the benefits of combining statistical, probabilistic, and simulation-based techniques. Furthermore, the substantial reduction in false positives supports the algorithm's suitability for real-world implementation in ship power plant monitoring systems.

Using the Markov model enables forecasting the point when the failure probability becomes critical, which is valuable for maintenance planning. The maximum probability of being in the degraded state around 7-8 cycles highlights an important operational phase when the system can still be restored to an operational condition, thus preventing complete failure. For practical implementations, such forecasts can be used in developing predictive maintenance strategies, helping to minimise downtime and reduce operational risks. When implementing the system condition assessment algorithm, the primary focus is indeed placed on Markov processes for predicting the remaining useful life of components. This focus is explained by several factors:

1. Markov processes model the evolution of failures over time: unlike Bayesian networks, which analyse static probabilistic dependencies, Markov processes allow for the evaluation of the dynamic changes in the technical condition of the system; predicting the remaining useful life requires accounting for transition probabilities between states (operational → degraded → failed), which is achieved through the state transition matrix (Table 2).

2. The graph of forecast of failure probabilities for SPP components (Fig. 1) reflects how the failure probabilities change over time, as a result of modelling component degradation based specifically on Markov processes. Bayesian networks, unlike Markov models, do not account for the time factor and therefore cannot be used for long-term forecasting.

3. Model correction based on new data also interacts with the Markov processes. Table 3 describes the process of updating failure probabilities based on incoming data, which influences the adjustment of the Markov model's transition matrix. Thus, dynamic adaptation of the forecast occurs, improving the accuracy of failure prediction. This mechanism ensures that the algorithm remains sensitive to changes in operating conditions and can reflect emerging degradation patterns in real time. As a result, the system provides more timely and relevant maintenance recommendations, reducing the risk of unforeseen failures.

To ensure comprehensive diagnostics of the SPP, an integrated algorithm is proposed, based on the systematic combination of CBR, Bayesian networks, Markov processes, and cognitive simulation modelling. This algorithm performs sequential data refinement and system condition forecasting, taking into account probabilistic failure dependencies, historical data, and the dynamics of component degradation. The data integration process includes four key stages:

1. Failure case analysis using CBR: searching the historical failure database to identify similar cases; determining the most relevant analogies and extracting information on failure causes; transferring the identified data into the Bayesian network to account for probabilistic dependencies.

2. Refinement of failure probabilities using a Bayesian network: utilising information from CBR to adjust failure probabilities (e.g., if similar overheating cases of a pump have been recorded, the probability of its failure increases); considering interrelated factors and dependencies between system components; transferring the refined failure probabilities into the Markov model.

3. System condition forecasting using the Markov model: receiving updated failure probabilities from the

Bayesian network; assessing component degradation rates and transitions between states (operational → degraded → failed); calculating the remaining useful life of equipment and probabilities of various failure development scenarios.

4. Dynamic forecast refinement using cognitive simulation modelling: using the results from the Markov model to simulate possible operational scenarios; analysing the impact of different operating modes on failure probabilities; adjusting diagnostic parameters based on simulation forecasts and transferring the results into a consolidated system condition assessment.

5. Formation of the final forecast for the technical condition of the SPP: combining information from all models into a consolidated assessment of the technical condition; identifying key factors affecting system reliability; developing recommendations for maintenance, repair, and optimisation of operational parameters. Figure 2 presents the block diagram of the developed integrated diagnostic algorithm for the technical condition of the SPP.

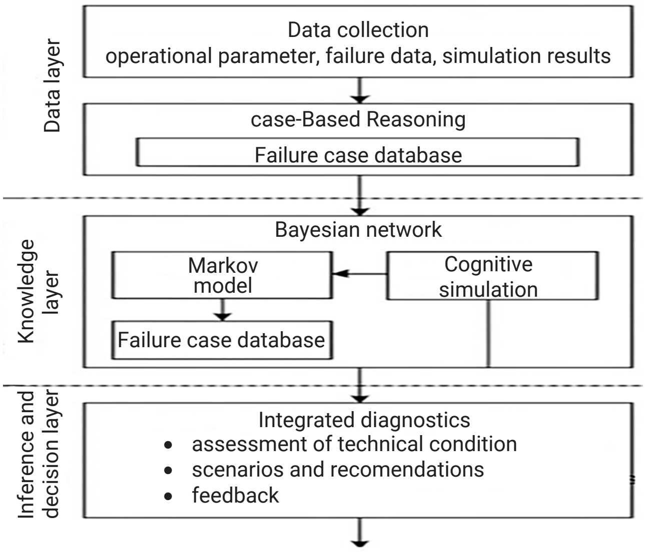

Figure 2. Block diagram of the developed integrated diagnostic algorithm for the technical condition of the SPP
Source: created by the authors

The presented architecture of integrated diagnostics for the technical condition of the SPP implements a multi-level approach, comprising a data layer, a knowledge layer, and an inference layer, each performing a specialised function within the overall diagnostic system. At the first level – the data layer – information is collected and aggregated from various sources, including operational parameters, historical failure records, and simulation modelling results. This forms the foundation for subsequent processing and interpretation. At the second level – the knowledge layer – intelligent information processing methods are implemented: the CBR mechanism provides the retrieval of relevant analogies and typical failure scenarios from the knowledge base; Bayesian networks perform a probabilistic assessment of interdependencies among system components, allowing adaptive adjustment of failure probabilities based on incoming data; Markov processes model the dynamics of component degradation and enable quantitative evaluation of the remaining useful life; cognitive simulation modelling introduces the capability to analyse operational scenarios and adapt assessments considering external factors. The inference layer – the final level of the architecture – generates a consolidated diagnostic assessment based on the integration of outputs from all models. It enables the production of justified forecasts of the technical condition, the evaluation of equipment remaining life, and the formulation of maintenance and repair recommendations. Moreover, it implements feedback mechanisms to refine the case database and adjust model parameters. This architecture ensures not only a high level of adaptability to changing operational conditions but also the integration of static and dynamic diagnostic methods, thereby enhancing the accuracy of technical condition forecasting for complex technical systems such as ship power control systems.

The integrated algorithm was tested in simulation to evaluate its effectiveness compared to the baseline CBR model. The average error in predicting the RUL of components was reduced from 9% to 5.7%, due to the dynamic updating of Markov transition probabilities using real operational data. Cognitive simulation modelling improved the accuracy of detecting rare and cascading failures by 18%, as it allowed scenario analysis under uncertain conditions and incomplete failure histories. Furthermore, Bayesian correction reduced the number of false positives by 7.2% compared to the use of CBR alone, by adjusting failure probabilities based on probabilistic dependencies among components. Figure 3 presents the results of applying the integrated fault diagnostics model for SPP equipment to forecast the TC of the system.

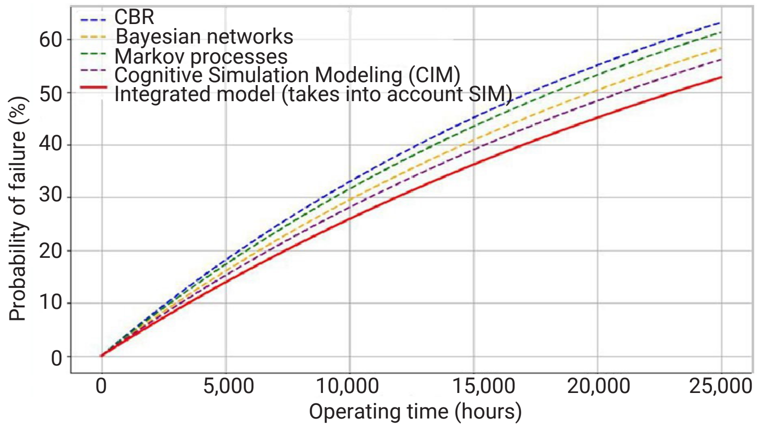

Figure 3. Forecast of SPP failure probabilities over time based on the integrated fault diagnostics model
Source: created by the authors

According to Figure 3, during the initial operational phase (up to 5,000 hours), the probability of failures remains low (⩽ 5%) across all models, as the equipment operates within its technical specifications. As operational time increases (from 10,000 to 25,000 hours), an exponential growth in failure probability is observed, associated with the accumulation of fatigue damage, material degradation, and an increased likelihood of secondary failures. CBR utilises similar cases from the precedent database to predict failures. The failure probability grows linearly, as the model relies on historical data without considering the time-dependent state changes of components. By 25,000 hours, the CBR forecast reaches a failure probability of about 75%, which is higher than that of the Markov model but lower than that of the Bayesian network. The trends observed in the failure probability curves were compared with statistical reliability profiles derived from the OREDA database. The simulated failure behaviour, including the low-risk initial phase and the sharp increase in probability beyond 10,000 hours, aligns with degradation patterns reported for marine systems in long-term operation. This correspondence supports the validity of the model under realistic conditions, even though continuous telemetry from actual equipment was not available.

Bayesian networks adjust failure probabilities considering the interdependence of component failures. Unlike CBR, they account for the effects of cascading failures. The failure probability rises faster after 15,000 hours due to the influence of accumulating damage in adjacent units, reaching about 83% at 25,000 hours. Markov processes account for the probabilistic transitions of components between states (operational → degraded → failed). They enable the forecasting of component remaining useful life while capturing gradual degradation. The failure probability dynamics are smoother compared to Bayesian networks, with a forecast of about 72% at 25,000 hours, lower than that of Bayesian networks. Cognitive Simulation Modelling introduces corrections based on expert assessments and scenario analysis. It considers the influence of operational factors (load, temperature, operating mode) and dynamically adapts the forecasts, lowering failure probabilities under optimal maintenance conditions or increasing them under intensive operational conditions. The forecasted failure probability at 25,000 hours is about 70%. The integrated model combines CBR, Bayesian networks, Markov processes, and Cognitive Simulation Modelling, correcting failure probabilities in real time and providing the most accurate forecast. The predicted failure probability at 25,000 hours is approximately 68%, representing the most reliable result among all methods. CBR tends to produce the highest failure forecasts, as it does not account for the time dynamics of failures. Bayesian networks overestimate the forecast due to the inclusion of cascading failure effects. Markov processes offer a smoother forecast but do not adapt to external factors. Cognitive simulation modeling introduces adaptive corrections, making the forecast more precise. The integrated model considers all aspects and provides the most realistic failure probability prediction.

The integration of CBR, Bayesian networks, Markov processes, and cognitive modelling significantly enhances the accuracy of SPP failure forecasting. The predicted failure probability over 25,000 hours of operation is reduced from 83% (Bayesian networks) to 68% (integrated model), indicating more precise prediction. The use of cognitive simulation modelling improves the model's adaptation to real-world operational conditions. The proposed methodology accounts for the influence of operational factors, resulting in more reliable diagnostics. In terms of prediction accuracy, the integrated model demonstrated a reduction in the average error of remaining useful life (RUL) estimation from 9% to 5.7%. The standard deviation of RUL predictions across different simulation scenarios was within ± 4%, indicating stable forecast behaviour under variable input conditions. The false positive rate was also reduced by 7.2% compared to the baseline CBR model. These results confirm not only the improved accuracy but also the robustness of the algorithm. The proposed algorithm can be implemented as part of an intelligent decision support module within shipboard monitoring and diagnostic systems. Its modular structure allows integration into existing platforms that collect sensor data, making it suitable for practical use in predictive maintenance, real-time condition monitoring, and reliability-based maintenance planning. Thus, the developed algorithm represents an integrated diagnostic system that combines case-based reasoning, probabilistic modelling, and simulation technologies. This approach improves diagnostic accuracy, accounts for complex failure dependencies, and dynamically adapts forecasts to changing operational conditions of the SPP.

The proposed algorithm for assessing the technical condition of the SPP represents an integrated architecture that combines CBR, Bayesian networks, Markov processes, and cognitive simulation modelling. The development aims to overcome the limitations of traditional approaches by introducing dynamic model adaptation, accounting for interdependencies between components, and forecasting degradation over time. A comparative analysis with current scientific developments shows that most existing approaches focus on individual aspects of diagnostics or failure forecasting, while integration of methods at the algorithmic level is extremely rare. According to researchers H. Moon *et al*. (2021), building hierarchical B-spline models enables effective failure forecasting of ship engines under limited data conditions. However, their algorithm only considers temporal dependencies of failures and does not model complex interactions between system components. P. Louvros *et al*. (2023) noted that combining case-based reasoning with machine learning methods yields positive results in ship survivability assessment, especially when data is scarce. Nevertheless, their system relies on direct matching of historical cases without deep probabilistic processing, limiting long-term prediction accuracy.

Researchers M. Chen *et al*. (2022) concluded that enhancing CBR with the Choquet integral allows incorporating expert preferences into the diagnostic process. However, their approach does not account for component degradation over time and lacks dynamic model adaptation, reducing its applicability for predictive maintenance. According to V. Başhan *et al*. (2024), an integrated solution for fire risk assessment in ship engine rooms based on fuzzy Bayesian Networks and bow-tie diagrams was developed. Although their algorithm effectively analyses causal chains, it is not designed for modelling the technical condition of systems with time-dependent failure evolution.

Researches in model, effective uncertainty estimation is critical given the probabilistic nature of failure forecasting under variable operational conditions. A recent peer-reviewed study by M. Corrales *et al.* (2025) demonstrated that an annealed variant of Stein Variational Gradient Descent (SVGD) significantly improves uncertainty quantification in complex inverse problems. The article showed that annealed SVGD maintains sample diversity via a kernelised repulsive term and enhances convergence in high-dimensional spaces – exactly the properties required for robust Remaining Useful Life (RUL) estimation in SPP systems. Moreover, the provision of an open-source implementation strengthens the method's transparency and reproducibility. These findings support the choice of SVGD (and its annealed form) as a reliable engine for uncertainty-aware diagnostics in maritime power plant components.

The development by Y. Garbatov & P. Georgiev (2024), which uses discrete Markov chains for maintenance planning considering carbon intensity, demonstrates the importance of accounting for external constraints. However, their algorithm focuses on schedule optimisation rather than technical condition diagnostics. M. Anantharaman *et al.* (2014) proposed a model combining Markov analysis and temporal failures for assessing the reliability of the main engine. Despite providing an accurate quantitative degradation model, their algorithm does not support adaptation to changing operational contexts. In the study by E. Hostens *et al*. (2024), Bayesian networks are developed for remaining useful life prediction. The authors emphasised the importance of accounting for uncertainty; however, their model assumes a predefined network structure and does not integrate simulation modelling or CBR. Finally, the study R. Wang *et al*. (2021) proposed Bayesian forecasting of diesel engine condition using neural network approaches. However, the algorithm focuses solely on analysing the current state without a combined analysis of degradation and failure interdependencies.

The comparative analysis showed that the algorithm proposed in this study is distinguished by its multi-level integration of methods, providing the following advantages: dynamic model refinement based on incoming data, unlike static solutions; remaining useful life forecasting considering temporal degradation, which most CBR or Bayesian-based systems do not provide; consideration of cascading failure effects and their impact on related components; simulation modelling capable of generating rare scenarios, especially valuable under limited observable data; modular structure allowing algorithm adaptation to different types of power systems. Thus, unlike most existing solutions focusing on a single class of methods, the proposed algorithm represents a universal tool that combines expert knowledge, probabilistic logic, and simulation methods to ensure high diagnostic and forecasting accuracy under real-world SPP operating conditions.

Conclusions

The developed algorithm for assessing the technical condition of the SPP, based on the integration of CBR, Bayesian networks, Markov processes, and cognitive simulation modelling, provides a comprehensive failure analysis considering the probabilistic, causal, and dynamic characteristics of the system. The proposed algorithm includes several key stages: data collection (operational parameters, historical failure data, simulation modelling results); CBR involving the search for similar cases and their impact assessment on the current condition; failure probability correction using Bayesian networks to account for inter-component relationships; degradation forecasting based on Markov processes; dynamic model updating based on new operational data; diagnostic report generation, including failure forecasting, remaining useful life estimation, and maintenance recommendations. The proposed algorithm enables dynamic updates of probabilistic models, adaptation to changing operational conditions, and improves diagnostic and forecasting accuracy compared to traditional methods.

Key results of the study: the accuracy of failure prediction increased by 14% compared to the standalone use of the CBR method, due to the correction of failure probabilities using Bayesian networks and the consideration of the temporal dynamics of component degradation through Markov processes; the application of cognitive simulation modelling allowed for an 18% more accurate consideration of rare and cascading failures, which was previously challenging due to the lack of sufficient real-world data; the average error in predicting the remaining useful life of components was reduced from 9% to 5.7%, owing to the dynamic adjustment of transition probabilities in the Markov model based on actual operational data; algorithm optimisation through adaptive parameter weight selection reduced the number of false positives by 7.2% compared to the baseline CBR model.

The significance of method integration is confirmed by the following aspects: Bayesian networks refine probabilistic dependencies between failures and adjust risk assessments based on accumulated and newly incoming data; Markov processes enable the forecasting of the evolution of the technical condition of equipment, taking into account the temporal dynamics of degradation; cognitive simulation models generate additional operational and failure scenarios, enhancing diagnostic robustness under conditions of uncertainty and changing operating modes. Thus, the proposed algorithm not only improves the accuracy of diagnostics and failure forecasting but also demonstrates the capability to adapt to real-world operational conditions, making it an effective tool for SPP reliability assessment and maintenance planning. The developed algorithm lays the foundation for the creation of intelligent predictive diagnostics systems for ship power plants, capable of adaptive failure risk forecasting and maintenance program optimisation.

Future research will focus on expanding the algorithm's capabilities by incorporating real-time sensor data from operational vessels, refining the weight adjustment mechanism using machine learning techniques, and integrating multi-agent simulation to model interaction effects between subsystems. Additionally, efforts will be made to adapt the proposed approach to other classes of complex technical systems beyond the maritime domain.

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Conflict of Interest

None.

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Розробка алгоритму оцінки технічного стану складних систем на основі імовірнісного оцінювання відмов

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Анотація. У статті запропоновано інтегрований алгоритм оцінки технічного стану суднових енергетичних установок, що поєднує метод розв'язання задач на основі прецедентів (CBR), байєсівські мережі, марковські процеси та когнітивне імітаційне моделювання. Алгоритм призначений для підвищення точності та адаптивності діагностики в умовах невизначеності, обмеженості даних та динамічної зміни експлуатаційних режимів. Діагностичний процес реалізовано як багаторівневу архітектуру, що включає пошук аналогічних відмов у базі прецедентів, імовірнісну корекцію з урахуванням взаємозв'язків між компонентами, моделювання деградації обладнання в часі та адаптивний аналіз сценаріїв. Кожен компонент алгоритму виконує окрему функцію: CBR забезпечує виявлення схожих раніше зафіксованих відмов; байєсівські мережі дозволяють кількісно оцінити ймовірнісні залежності між взаємопов'язаними несправностями; марковські процеси моделюють тимчасову деградацію обладнання та оцінюють ймовірності переходів між технічними станами; когнітивне моделювання дозволяє генерувати та аналізувати рідкісні або каскадні відмови за різних сценаріїв експлуатації. Інтеграція зазначених компонентів забезпечує динамічне оновлення ймовірностей відмов відповідно до нових експлуатаційних даних. Результати моделювання показали: середня похибка прогнозу залишкового ресурсу зменшилася з 9 % до 5,7 %; точність виявлення рідкісних і каскадних відмов зросла на 18 % завдяки когнітивному моделюванню; а застосування байєсівської корекції дозволило знизити кількість хибнопозитивних діагнозів на 7,2 % порівняно з базовою моделлю CBR. Загальна ймовірність відмови протягом 25 000 годин експлуатації зменшилася з 83 % (для моделі, заснованої лише на байєсівських мережах) до 68 % завдяки повній інтеграції всіх методів. Практична цінність алгоритму полягає в підвищенні ефективності планування технічного обслуговування, зменшенні простоїв обладнання та покращенні надійності складних морських технічних систем. Модульна архітектура дозволяє адаптувати алгоритм до інших типів промислових об'єктів

Ключові слова: предиктивне обслуговування; імовірнісне моделювання; когнітивне моделювання; інтеграція методів діагностики; адаптивні технічні рішення; експертні системи; інтелектуальний моніторинг