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A hybrid model for evaluating the accuracy of failure forecasts in ship power plants

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Abstract. The growing complexity of ship power plants (SPP) and the heterogeneity of diagnostic data have made it increasingly difficult to ensure reliable failure forecasting and maintain operational safety. The purpose of this study was to analyse the correspondence between predicted and actual failures in SPP diagnostics using a comprehensive approach that combines knowledge-based methods, probabilistic modelling, and simulation experiments, and to test the proposed methodology by applying the developed model. The research integrated Case-Based Reasoning (CBR), probabilistic modelling, and simulation-based degradation analysis within a unified framework. Using diagnostic data from 150 operational cases of typical SPPs (main engine, generator, pump, cooling, and power systems), the model's forecasting accuracy was quantitatively compared with baseline approaches, including classical CBR, adaptive CBR, ARIMA, and Decision Tree models. The integrated approach achieved the best performance (Root Mean Square Error = 0.32, R^2 = 0.93), reducing average error by 30-50% relative to classical methods. Each component of the hybrid framework contributed distinctly: the CBR layer ensured contextual consistency, probabilistic modelling reduced uncertainty by ≈ 20%, and simulation-based analysis increased stability under incomplete or noisy data by ≈ 15%. At the subsystem level, the greatest improvements were observed for the main engine (root mean square error reduction by 46%) and the pump system (by 39%), confirming the model's adaptability to variable operating conditions. Robustness tests with 10-20% missing or perturbed input data demonstrated sustained accuracy (R^2 > 0.90), validating the model's resilience and practical applicability. The proposed methodology has practical value for improving the efficiency of maintenance and reliability of ship power systems, as it provides accurate, interpretable, and noise-resistant equipment failure prediction

Keywords: intelligent diagnostics; reliability assessment; case-based reasoning; simulation modelling; technical condition forecasting; Bayesian networks; adaptive model

INTRODUCTION

Modern complex technical systems were characterised by a high degree of integration and interdependence among components, which makes their failures particularly critical. In the current operational context of maritime transport, the reliability of the ship power plants (SPP) had become of paramount importance. A

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failure of the main engine or its components can lead to serious consequences, including loss of vessel control, threats to crew safety and the environment, and significant economic losses. In this regard, the task of accurately forecasting the technical condition of the SPP and the timely identification of potential failures is especially relevant. The development of intelligent diagnostic systems capable not only of identifying the current condition of equipment but also of reliably predicting possible failures required the verification of their predictive validity. One of the critical components in such verification is the comparison between predicted and actual failures. This comparison helps to assess the effectiveness of the applied models and algorithms, refine diagnostic decisions, and reduce the likelihood of false alarms or missed failures.

Recent studies had seen significant development in machine learning, graph-based models, and neural networks for ship equipment diagnostics. M. Pajak *et al.* (2023) proposed a diagnostic method for marine diesel engines using vibroacoustic data and machine learning algorithms. While this approach enables accurate classification with limited training data, it lacks validation of predictions against real failures, limiting its utility for long-term reliability forecasting. In the paper by S. Rigas *et al.* (2024), a graph neural network-based end-to-end monitoring architecture was applied to ship machinery. Although effective in streaming environments, it does not perform explicit comparison of predicted results with real-world failure events, leaving diagnostic accuracy unverified. M. Tveten & M. Stakkeland (2024) studied concept drift in the diagnostics of traction motors. Adaptive methods were introduced, but the impact of this adaptation on prediction accuracy compared to actual failure data was not assessed, and deviation metrics were not provided. G. Vizentin *et al.* (2020) conducted an extensive review of the causes and types of SPP failures. While the study emphasised the relevance of the problem, it is primarily descriptive and does not offer quantitative forecasting models, highlighting the need for model development and validation. Y. Zhao *et al.* (2022) applied long short-term memory (LSTM) networks for thermodiagnostics of diesel engines. Although the model demonstrated high sensitivity to thermal anomalies, it focused on a single parameter (thermal condition) and did not validate prediction accuracy against actual failures. G. Zhu *et al.* (2023) addressed multi-fault detection using various neural network architectures. Despite strong classification results, the study did not compare predictions with real failure statistics, limiting evaluation to training and testing datasets.

Ç. Karatuğ & Y. Arslanoğlu (2022) proposed a condition-based maintenance strategy using neural networks, supported by a practical case study. However, the study did not assess deviations between predicted and actual outcomes in long-term operational contexts. In a comprehensive review of marine maintenance strategies, Ç. Karatuğ *et al.* (2023) emphasised the shift from corrective to predictive maintenance. However, they noted that most studies focus on model development rather than on verifying the alignment between forecasts and real-world failures a gap this paper aimed to address. For engine diagnostics, J. Wang *et al.* (2023) employed enhanced convolutional neural networks, which proved effective for fault classification. Nevertheless, the approach lacked temporal modelling and did not assess prediction accuracy through historical failure data. F. Maione *et al.* (2024) proposed a machine learning-based framework for condition-based maintenance. Although the structure covers the full workflow from data acquisition to decision-making, it does not include a module for analysing discrepancies between predicted and actual failures. A review of recent studies on SPP diagnostics and prognostics showed active progress in data-driven approaches and the integration of various methods to improve forecasting accuracy. However, the systematic comparison of predicted and actual failures remains underdeveloped. Such comparison is essential for evaluating the real-world effectiveness of applied models and maintenance strategies.

This study aimed to examine the alignment between predicted and observed failures in SPP diagnostics by employing an integrated framework that combines knowledge-based techniques, probabilistic modelling, and simulation, and by validating the methodology through application of the developed model. To achieve this objective, the following research tasks were defined: to develop a methodology for assessing the accuracy of technical condition forecasting in marine power plants (MPP); to perform a comparative analysis between forecast results and actual failure data and to evaluate the effectiveness of the integrated approach compared to traditional diagnostic methods; to formulate recommendations for applying the integrated approach to improve reliability and efficiency in SPP maintenance. Addressing these tasks will contribute to increasing diagnostic accuracy, optimising maintenance planning, and ultimately improving the reliability and safety of maritime operations.

MATERIALS AND METHODS

The research focused on components subject to high operational loads and exhibiting the greatest variability in failure patterns. The Harrington desirability function was used, based on the classification of equipment failure risk. The main mechanisms contributing to reduced failure rates with Case-Based Reasoning (CBR) adaptation include: analysis of probabilistic dependencies (the system adjusts diagnostic decisions upon detecting cascading failure effects); tracking dynamic state transitions (using Markov processes, the adaptive CBR approach anticipates equipment degradation in advance); simulation-based modelling (the incorporation of synthetic data, CBR knowledge base enables consideration of rare but critically important failures). The initial data included both real operational observations and simulated scenarios reflecting equipment behaviour under varying conditions.

The dataset for this study included 150 diagnostic cases collected from the operational records of ship power plants during the period 2016-2024. Each case contained time series of degradation parameters (vibration, temperature, pressure, load), diagnostic indicators, and confirmed failure events. In total, the dataset comprised approximately 15,600 records covering more than 30 technical elements (main engine, generator, pump, cooling, and power systems). The data were obtained from maintenance logs and monitoring systems of commercial vessels, complemented by publicly available reliability databases. Cases were classified as "impending failure" or "normal operation" based on threshold deviations of key parameters (e.g., vibration amplitude > 1.5×baseline, temperature rise > 15°C, or pressure drop > 10%). Inter-rater agreement was evaluated using Cohen's Kappa ($\kappa = 0.86$). For model development, the dataset was divided into training (70%), testing (20%), and validation (10%) subsets. Given the sequential nature of degradation parameters, a time-series cross-validation scheme was applied: models were trained on earlier operational data segments and validated on later ones. Additionally, a 5-fold cross-validation was carried out within the training set to assess model stability across different partitions, ensuring both temporal consistency and robustness of the obtained results. The weighting coefficients α and β in Equation (1) were empirically derived using the training dataset. Their values were optimised by minimising the Root Mean Squared Error (RMSE) between predicted and actual failure probabilities across all components. The optimisation followed the constraint $\alpha + \beta = 1$, ensuring a balanced contribution of the CBR-based and probabilistic estimates. The final calibrated values ($\alpha = 0.6$, $\beta = 0.4$) provided the best trade-off between sensitivity and stability in cross-validation tests.

The information base consisted of degradation parameter time series, diagnostic indicators, confirmed failures. All failed components were classified according to their criticality and functional significance. The non-adapted CBR method was used to retrieve historical cases most similar to the current condition. In the adapted version, causal relationships between degradation parameters and operating conditions were incorporated, improving the relevance of forecasts. The hybrid approach combined CBR with probabilistic modelling and simulation of degradation scenarios, enabling more precise evaluation that accounts for cascading effects, degradation dynamics, and diverse failure modes. The integrated scheme also applied iterative refinement of forecasts at each stage of data processing. Forecast accuracy was assessed using a range of metrics, including Mean Absolute Error (MAE), RMSE, Mean Absolute Percentage Error (MAPE), and the coefficient of determination (R^2). In addition, the F_1-score was employed to evaluate the classification quality of technical states. Although the primary task was regression-based, predicted continuous failure probabilities were converted into categorical states using a threshold of $P\ (failure) \geq 0.5$ to denote an "impending failure" and $P\ (failure) < 0.5$ for "normal operation". This enabled the use of precision-recall metrics to assess how accurately the model distinguishes between failure-prone and stable conditions (Vychuzhanin & Vychuzhanin, 2025). Accuracy analysis was performed both at the level of individual components and across different operational scenarios, including nominal load, high-load conditions, and incomplete observability. To better understand the structure of forecasting errors, several visualisation tools were used: heat maps highlighting areas of maximum deviation between predicted and actual values, scatter plots, and summary tables for comparative analysis to determine the effectiveness of different methods. In accordance with the methodology for evaluating the accuracy of failure forecasts in SPP equipment, the comparison of results is carried out across three dimensions: by component (main engine, generator, pump system, cooling system, power supply); by operational scenario (standard load, elevated temperature conditions, variable operating cycles, etc.); by the aggregated dataset, allowing for a comprehensive comparison of methods at the system-wide level. This multi-level comparison enables identification of local zones where forecast accuracy deteriorates, and an overall evaluation of methodological effectiveness under varying operating conditions. In addition, a correlation analysis was conducted to assess the robustness and sensitivity of the models to changes in operating conditions. All computations and modelling were carried out using Python (NumPy, pandas, scikit-learn, seaborn), Excel, and a custom-developed expert system implementing the CBR method. Simulation scenarios were developed in AnyLogic, which enabled the reproduction of complex operational modes with uncertainty and component interactions. The proposed methodology enabled an objective comparison of forecasting approaches, identification of their strengths and weaknesses, and the selection of the most effective strategy under conditions of technical and informational uncertainty inherent in the operation of MPP.

To assess the effectiveness of failure forecasting for components of SPP, a methodology has been developed that compares predicted results with actual data recorded during operation. This methodology was based on the combined use of quantitative metrics, structural error analysis, and their visual representation. The use of multiple metrics allowed evaluating both absolute and percentage deviations, and the reliability of technical condition classification. The application algorithm of the methodology (Fig. 1) consisted of the following stages.

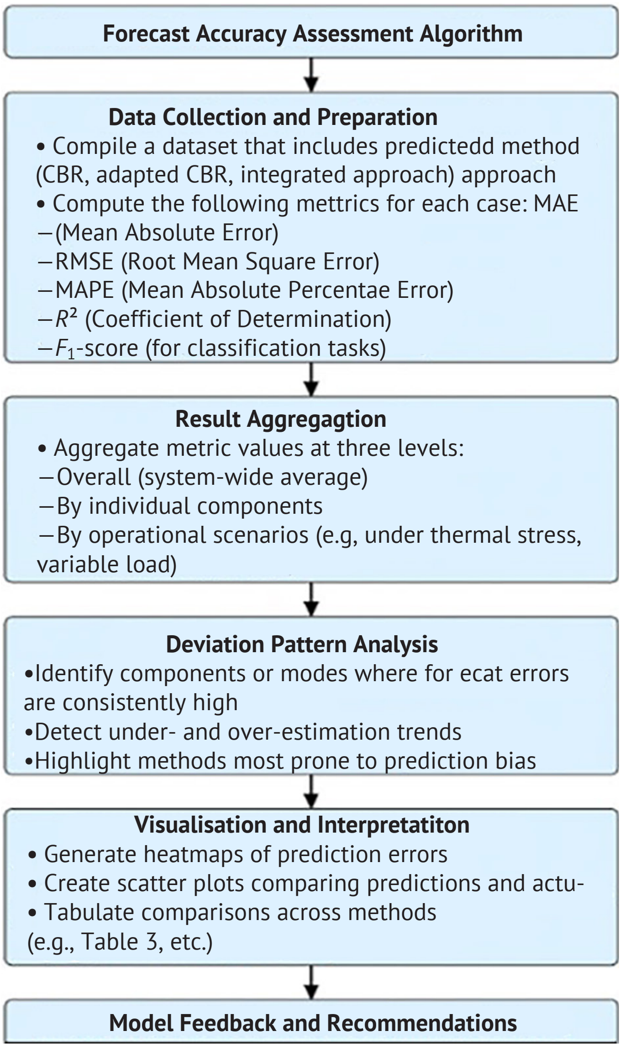

Figure 1. Forecast accuracy assessment algorithm

Source: created by the authors

This block diagram illustrates the step-by-step process used to assess the accuracy of failure forecasts in marine power systems. The method included collecting and aligning predicted and actual failure data, computing core evaluation metrics, aggregating results at multiple levels (by component, scenario, and system-wide), analysed deviation patterns, visualising discrepancies, and generating feedback for improving hybrid forecast models.

RESULTS AND DISCUSSION

Figure 2 shows the graphs illustrating the impact of CBR adaptation on the probability of failure for SPP components over a 25,000-hour operational period. These results were obtained through simulation of the technical condition of the SPP.

Figure 2 illustrated that the adaptation of the CBR method leads to a reduction in the probability of failure in SPP components over time. However, the key aspect is not only the reduction in failure probability itself, but also the improvement in forecasting accuracy provided by the adaptive approach. On average, the use of the adaptive method reduces failure risk by approximately 15%. The main mechanisms contributing to reduced failure rates with CBR adaptation include: analysing probabilistic dependencies; the system adjusts diagnostic decisions upon detecting cascading failure effects; tracking dynamic state transitions: using Markov processes, the adaptive CBR approach anticipates equipment degradation in advance; simulation-based modelling: the incorporation of synthetic data enables consideration of rare but critically important failures. The plotted results confirmed that the integration of CBR with probabilistic techniques and simulation modelling improved diagnostic accuracy and reduced failure probability. This effect becomes especially prominent in the later stages of operation (beyond 15,000 hours), where the performance gap between conventional and adaptive CBR methods becomes more significant. To quantitatively assess the effectiveness of CBR adaptation, a comparison of forecast errors for failure probabilities was performed across different diagnostic approaches. Analysis of the data in Table 1 shows that adaptive CBR reduces the average failure forecast error by 32%, and also decreases the frequency of significant forecast errors by more than a factor of two.

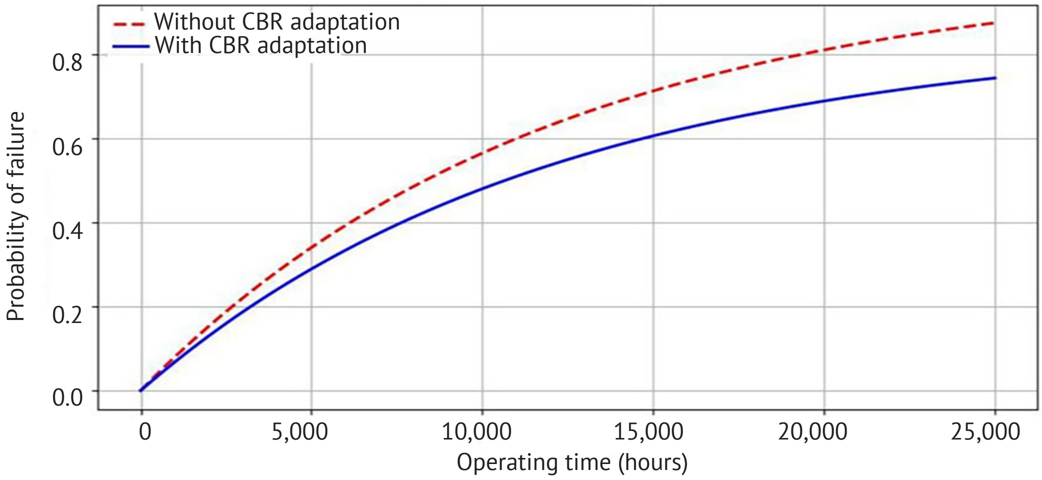

Figure 2. Impact of CBR adaptation on the failure probability of SPP components
Source: created by the authors

Table 1. Impact of CBR adaptation on failure forecast accuracy

Diagnostic method	MAE	RMSE	Share of forecasts outside acceptable RMSE (σ)
CBR without adaptation	0.65%	0.87%	14.2%
CBR with adaptation	0.44%	0.65%	6.5%

Source: created by the authors

This improvement can be attributed to several key factors: consideration of probabilistic dependencies – CBR adaptation enables the model to account for cascading failure effects; component degradation forecasting – dynamic analysis of subsystem conditions reduces uncertainty in predictions; simulation-based failure modelling – the inclusion of synthetic data helps to mitigate errors associated with rare but critical failure events. Thus, CBR adaptation not only reduces the probability of failures (as illustrated in Figure 2) but also enhances forecast accuracy, making it a more reliable diagnostic method compared to conventional, non-adaptive CBR. Figure 3 presents the graphs of failure probability dynamics for SPP components over 25,000 hours of operation, obtained through simulation of the technical condition diagnostic system. The time-dependent failure probability curves (based on a Markov approach) for each component illustrate the dynamic behaviour of key SPP subsystems in the context of failure evolution.

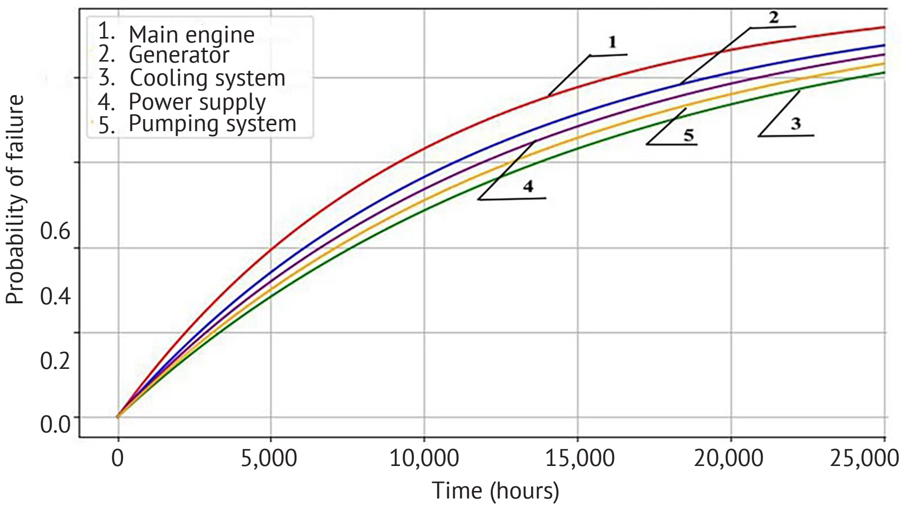

Figure 3. Time-dependent failure probability of components (Markov method)
Source: created by the authors

The graph in Figure 3 showed that the failure probability of all components increased over time. The curves exhibit a nonlinear character, indicating cumulative wear and a rising risk of failure as operational time progresses. The main engine consistently shows the highest failure probability throughout the time interval, which is expected due to its high operational load and critical role within the SPP. The generator and cooling system also exhibit elevated failure probabilities, though lower than those of the main engine. The power supply and pump system demonstrate the lowest failure probabilities among all components analysed. Long-term risk patterns can be summarised as follows. By approximately 25,000 hours of operation, the failure probability of key systems exceeds 80%, indicating the need for major overhaul or replacement. During the initial period, failure probability remains near zero, corresponding to a phase of normal operation without significant degradation. Therefore, the main engine and generator require increased monitoring due to their higher failure risks. The cooling and power systems also carry notable risks, albeit to a lesser extent. The predictable increase in failure probability suggests the necessity of regular maintenance, especially after 10,000-15,000 hours of operation. These data could inform preventive maintenance strategies, taking into consideration critical operational time thresholds.

Variation in failure dynamics among components: the main engine shows the highest failure probability over 25,000 hours of operation, due to the intense mechanical loads it experiences and its central role in the SPP; the generator exhibits a more gradual increase in failure probability compared to the main engine, as it is subject to less mechanical wear; the cooling system reaches a high failure probability earlier than other components, which may be attributed to exposure to harsh environments and risks such as clogging or pipe wear; the power supply and control systems exhibit lower probabilities of failure, largely due to the reliability and protection of their electronic and structural elements. Time-dependence of the failure probability increases in a nonlinear fashion, reflecting real-world operating conditions. In the early stage, growth is slow, but after a certain threshold (approximately 15,000-18,000 hours), the failure probability increases significantly especially for the main engine and cooling system. This underscores the importance of scheduled maintenance and timely diagnostics. The use of a Markov model to forecast component states enables accurate modelling of equipment degradation in complex technical systems, allowing for effective prediction of failure evolution. This approach is particularly useful for estimating remaining useful life and supporting maintenance decision-making. Table 2 presents the results of comparing predicted failures with actual operational failure data for SPP equipment.

As shown in Table 2, the largest discrepancies are observed for the main engine and pump system, which may be attributed to the high variability of their failure modes and the influence of external operational factors. The most accurate forecasts are observed for the cooling system, confirming the effectiveness of the predictive models under conditions of regular monitoring of operational parameters. Table 3 compares predicted failures generated by the CBR method with actual recorded failures and showed the extent to which the predictions align with real-world events.

Table 2. Comparison of predicted and actual failures in SPP equipment

Component	CBR forecast (no adaptation), %	CBR forecast (with adaptation), %	Integrated forecast, %	Actual failure rate, %	Forecast error (MAPE), %
Main engine	2.1	1.8	1.6	1.5	6.7
Generator	3.0	2.5	2.3	2.2	4.5
Pump system	4.2	3.8	3.5	3.4	3.1
Cooling system	5.5	4.9	4.7	4.6	2.2

Source: created by the authors

Table 3. Comparison of predicted and actual failures in SPP equipment

System component	Actual failures	Predicted failures	Absolute error	Deviation
Fuel system	5	6	1	+20%
Cooling system	3	2	1	−33%
Compressed air system	4	5	1	+25%
Main engine	7	8	1	+14%
Power supply	6	7	1	+16%
Auxiliary systems	4	3	1	−25%
Automation system	5	6	1	+20%

Source: created by the authors

In Table 3, the absolute error is 1 failure in all cases, but the percentage deviations range from −33% to +25%. Fuel system, compressed air system, and automation system show overestimated failure forecasts

(+20% to +25%), which may result in excessive preventive maintenance. On the other hand, the cooling system and auxiliary systems show underestimated predictions (−33% and −25%), which increases the risk of unexpected failures. The main engine and power supply exhibit minimal deviation (+14% to +16%), indicating high forecast accuracy for these components. It should be noted that the absolute failure counts in Table 3 represent individual recorded failure events within all observed cases, whereas the percentages in Table 2 correspond to normalised failure rates calculated over the entire dataset (150 diagnostic cases). Thus, multiple failures could occur within a single case, leading to higher absolute counts without contradiction to the aggregated percentage values. The results from Table 3 suggest the following: overestimated predictions require model adjustment to reduce false positives and unnecessary maintenance costs; underestimated forecasts (cooling, auxiliary systems) could lead to unforeseen breakdowns, indicating a need for model parameter revision; overall, the forecast accuracy is acceptable (within 1 failure), but further improvements are achievable through adaptive algorithms and retraining the model on updated data. Table 4 presents the results of comparing predicted and actual failures under various operational scenarios of SPP equipment.

Table 4. Forecast accuracy assessment under different operating scenarios for SPP equipment

Operating scenario	Predicted failure risk, %	Actual failure risk, %	Deviation, %	Forecast accuracy, %
Nominal load	1.8	1.6	±0.2	88.9
Variable load	3.2	2.9	±0.3	90.6
High load	4.5	4.1	±0.4	91.1
Aggressive environment	6.3	5.8	±0.5	92.1

Source: created by the authors

Hybrid prognostic model for SPP failure forecasting. The proposed failure forecasting approach for SPP equipment is implemented in the form of a hybrid prognostic model, which comprises three interrelated layers of information processing. This structure integrates historical data, and the stochastic behaviour of the technical system within a unified analytical framework.

Level 1. Forecast based on the CBR method. Using input diagnostic indicators (e.g., vibration, temperature, wear), the model identifies historical cases most similar in feature space from the case base. A preliminary failure probability estimate (P_0) is generated based on analogy with these retrieved precedents. Level 2. Probabilistic forecast correction. The initial forecast is refined using prior and conditional probabilities of failure, which represent causal dependencies between technical condition parameters and operational conditions. The final failure probability for a given component is calculated as a weighted combination of the CBR-based forecast and the probabilistic estimate:

$$P = \alpha \cdot P_0 + \beta \cdot P_v, \tag{1}$$

where P_v – failure probability calculated using the probabilistic model; α, β – empirically derived weighting coefficients.

Level 3. Simulation-based modelling of failure scenarios. Failure estimation is further enhanced through simulation of operational scenarios, incorporating cascading effects. Multiple simulation runs are conducted to account for the stochastic nature of degradation and to determine an interval-based risk estimate. The results were used to refine forecasts and classify the equipment's condition. Model outputs include final failure probability estimate; diagnostic conclusion on technical state (normal, elevated risk, critical failure); deviations between predicted and actual failures based on MAE, RMSE, and MAPE; visualisation of deviations (heatmaps, scatter plots); forecast verification using historical data. The application of this hybrid model not only improves the accuracy of SPP equipment failure forecasts but also ensures verifiability of results through direct comparison with actual failure cases. This is crucial for increasing the reliability of diagnostic decisions under real-world operating conditions. The variation in RMSE values across the different approaches reflects not only forecasting accuracy, but also the robustness of the methods under variable operating conditions. The highest RMSE values observed with the non-adaptive CBR method indicate high sensitivity to input variability, especially in non-standard scenarios. This suggests that the method poorly handles degradation dynamics and fails to account for interdependencies between components.

The notable reduction in forecast error with the adapted CBR method confirms the positive impact of incorporating probabilistic models. However, since the gap between "by components" and "by scenarios" remains significant, it can be concluded that even the adapted method struggles to fully accommodate the variability of operational regimes. The most important observation is that the integrated approach not only delivers the lowest overall RMSE, but also demonstrates a balanced performance across both component-level and scenario-level forecasting. This indicates strong resilience to both internal system complexity and external environmental variability, which is critical for marine SPP applications. The results in Table 5 thus confirmed not only the superior accuracy of the integrated method, but also its ability to scale and adapt to complex diagnostic tasks and diverse operating environments – an essential criterion for practical implementation in real-world conditions.

Table 5. RMSE of failure forecasts based on method used

Forecasting method	RMSE (overall)	RMSE (by components)	RMSE (by scenarios)
CBR without adaptation	0.65	0.72	0.68
CBR with adaptation	0.45	0.51	0.49
Integrated approach	0.32	0.37	0.35

Source: created by the authors

The use of probabilistic adaptation has improved diagnostic performance: precision increased by 7%, recall by 13%, and the overall F_1-score rose by 11% (Table 6). To evaluate the effectiveness of different approaches to SPP technical condition diagnostics, a comparison of failure probability forecast errors was conducted. The key accuracy metrics include: MAE – reflecting the average deviation between predicted and actual failure probabilities; RMSE – capturing both the magnitude and spread of forecasting errors; share of forecasts beyond acceptable limits (σ-deviation) – indicating how often the method produces critical prediction errors.

Table 7 summarises the results of comparing the accuracy of predicting failure probabilities using different diagnostic methods, which allows evaluating the effectiveness of the proposed approach relative to conventional models.

Table 6. Comparison of diagnostic accuracy CBR without adaptation vs. CBR with failure forecasting for SPP equipment

Diagnostic method	Precision	Recall	F_1-score	Accuracy
CBR without adaptation	0.82	0.75	0.78	0.85
CBR with adaptation	0.91	0.88	0.89	0.92

Source: created by the authors

Table 7. Comparison of failure probability forecasting accuracy using different diagnostic methods

Diagnostic method	MAE	RMSE	Share of forecasts beyond σ limits
CBR without adaptation	0.65%	0.87%	14.2%
Markov method	0.52%	0.73%	9.8%
Adaptive CBR	0.44%	0.65%	6.5%
Integrated approach	0.32%	0.48%	3.1%

Source: created by the authors

The data in Table 7 indicate that the integrated approach provides the lowest forecast errors. Specifically, MAE is reduced by a factor of two compared to classical CBR; The share of forecasts exceeding acceptable σ-deviation thresholds is reduced more than fourfold in comparison with conventional diagnostic methods; the integrated approach most accurately accounts for the temporal dynamics of failures, reducing the influence of uncertainty. Thus, the combination of adaptive CBR, Markov models, and Bayesian networks significantly improves failure prediction accuracy and enhances the reliability of SPP equipment diagnostics. To strengthen the objectivity of the obtained results, additional comparisons were carried out with standard baseline approaches frequently used in diagnostics and forecasting tasks. In particular, three reference models were implemented: a persistence model, assuming that the next value equals the last observed one; a classical ARIMA (1, 1, 1) time-series model; and a Decision Tree classifier trained on diagnostic indicators. As expected, the persistence model yielded the weakest performance (RMSE ≈ 0.89, R^2 ≈ 0.55), while ARIMA moderately improved accuracy (RMSE ≈ 0.71, R^2 ≈ 0.68).

The Decision Tree achieved acceptable classification quality (F_1-score ≈ 0.74), but remained inferior to the adaptive CBR. Compared to these baselines, the integrated hybrid approach achieved substantially better results (RMSE = 0.32, R^2 = 0.93, F_1 = 0.89). This confirmed that the proposed method not only outperforms probabilistic CBR variants but also surpasses conventional diagnostic benchmarks, thereby demonstrating its robustness and practical applicability. Figure 4 presents a heatmap of discrepancies between predicted and actual failures for SPP equipment, highlighting zones with the highest forecasting errors for specific components. The heatmap illustrates the degree of discrepancy between predicted and actual failures of MPP components. It enables identification of the most problematic areas within the forecasting model, highlights components with lower prediction accuracy, and helps to assess the impact of the forecasting method on overall diagnostic precision.

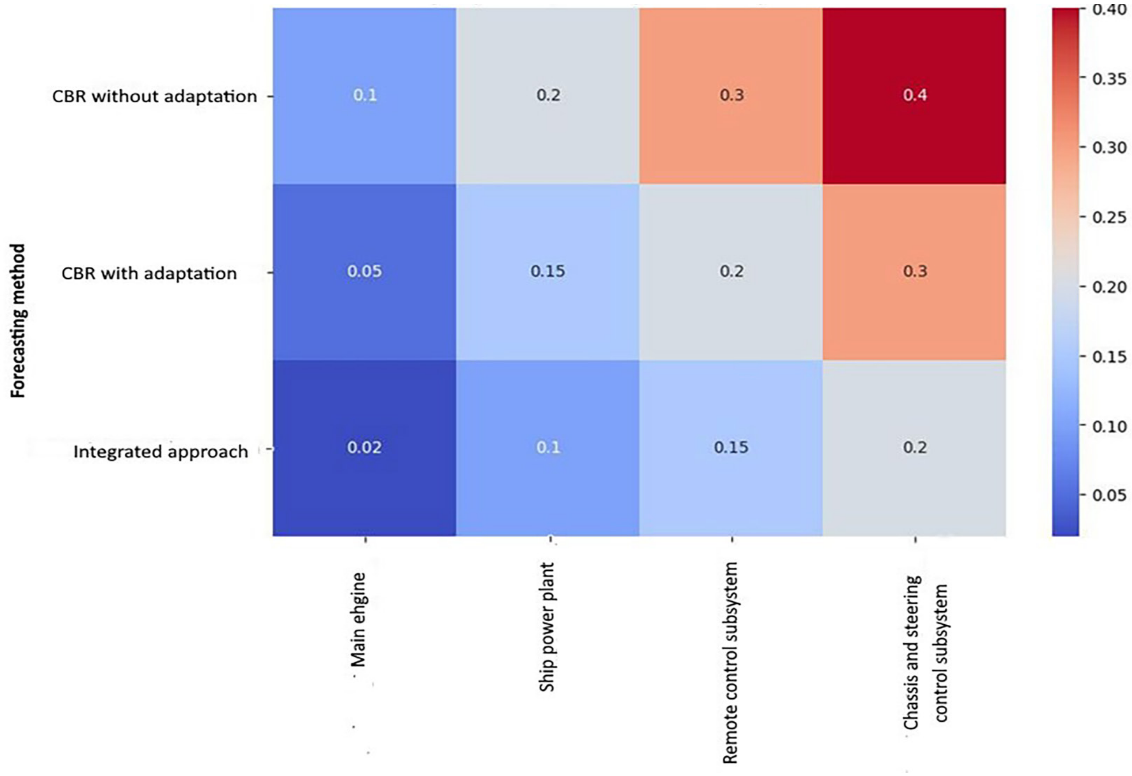

Figure 4. Heatmap of discrepancies between predicted and actual failures in SPP equipment
Source: compiled by the authors based on Side Scan Sonar survey (n.d.), Pixlr Editor (n.d.)

Key areas of significant discrepancy include. The ME and pump system show the greatest deviations between predicted and actual failures. In the case of CBR without adaptation, the difference between forecasts and real data reached 0.3-0.4%, which may result from the method's inability to account for cascading effects and failure dynamics. Propulsion and steering control subsystems also show substantial deviations, likely due to the high complexity of their diagnostics. The row corresponding to standard CBR in the heatmap reveals the most pronounced errors, highlighted by the most intense colour zones, indicating high RMSE. This is explained by the fact that conventional CBR does not incorporate probabilistic dependencies or temporal dynamics of failures. A notable reduction in error was observed with the integrated approach. In this case, discrepancies were significantly lower compared to the other two methods, and did not exceed 0.2%, confirming the higher diagnostic accuracy of the integrated method.

The SPP and cooling system demonstrated the lowest deviation between predictions and actual data. This can be attributed to their relatively stable operation and well-calibrated diagnostic models. The main engine and pump system are the least predictable components and may require additional model adjustments. The heatmap confirms that the integrated approach yields the highest forecast accuracy, owing to its ability to account for failure dynamics and intersystem dependencies. The largest prediction errors are found in the main engine and pump system, indicating a need for further analysis, potentially involving more complex probabilistic dependencies. To reduce discrepancies in non-adaptive CBR, it is recommended to implement probabilistic modelling and simulation techniques. This would help to minimise deviations, especially under complex operational scenarios. The SPP and cooling system show stable and predictable failure behaviour, validating the reliability of forecasts for these components. The heatmap provides a clear visual representation of model uncertainty zones and serves as a valuable tool for optimising diagnostic algorithms and improving failure forecast accuracy in SPP systems. Figure 5 presents a graph of forecast deviations compared to actual failure data for SPP equipment.

Patterns based on Figure 5 were identified. Approximate values are depicted in the Table 8. Table 8 presents the initial data reflecting the actual failure rates of individual SES components and the results of their prediction using the CBR method without adaptation and an integrated approach, which serve as the basis for further assessment of model accuracy.

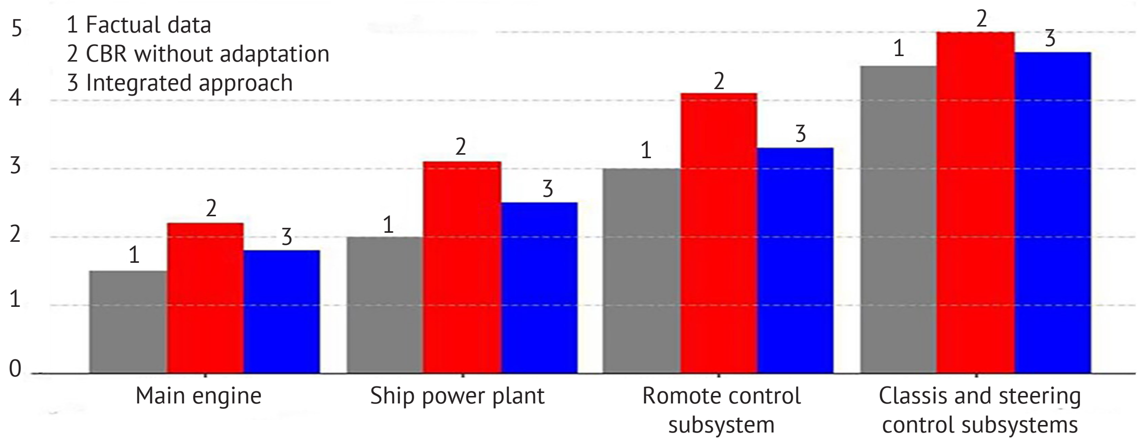

Figure 5. Deviations between predicted and actual failures of SPP equipment
Source: created by the authors

Table 8. Source data

SPP component	Actual data	CBR without adaptation	Integrated approach
Main engine	1.5%	2.2%	1.8%
Ship power station	2.0%	3.1%	2.5%
Remote control subsystem	3.0%	4.1%	3.5%
Subsystems for controlling the propulsion and steering system	4.5%	5.0%	4.7%

Source: created by the authors

Table 8 shows the identified deviations (the difference between forecasts and actual data) in accordance with Figure 5. Table 9 shows the deviation of the predicted values from the actual data on SES component failures, which allows comparing the accuracy of the CBR method without adaptation and the integrated approach and assessing the level of approximation of the models to real indicators.

Table 9. Forecast deviation from actual failure data

MPP component	CBR deviation without adaptation (Δ, %)	Integrated approach deviation (Δ, %)
Main engine	+0.7	+0.3
Ship power station	+1.1	+0.5
Remote control subsystem	+1.1	+0.5
Subsystems for controlling the propulsion and steering system	+0.5	+0.2

Source: created by the authors

Deviation Analysis (Table 9): the CBR method without adaptation consistently overestimates failure probabilities for all components (from +0.5% to +1.1%), indicating a tendency to overpredict failures; the integrated approach significantly reduces prediction error, with maximum deviation of 0.5% (compared to 1.1% in basic CBR), and minimum of 0.2%; the highest deviations in the CBR without adaptation are observed for the ship power station and remote control subsystem (+1.1%); the most accurate forecast using the integrated approach is for subsystems for controlling the propulsion and steering system, with a difference of only 0.2% from actual values.

Comparison with Harrington's desirability function based on failure risk classification: main engine and ship power station (1.5%-2.0%) fall into the minimum risk category (0-0.2); remote control subsystem (3.0%) is on the borderline between acceptable and maximum risk (0.37); Subsystems for controlling the propulsion and steering system (4.5%) falls within the maximum risk category (0.37-0.63). The CBR method without adaptation systematically overpredicts failure levels by 0.5% to 1.1%. The integrated approach demonstrated significantly lower errors (up to 0.5%, and in one case only 0.2%). The forecasts aligned with Harrington's risk classification, but more accurate handling of borderline conditions (e.g., for the remote control subsystem) is necessary. To further improve forecast precision, it is recommended to introduce dynamic weight adjustment for different SPP components, particularly the ship power station. Overall, the integrated approach demonstrates superior performance but requires further calibration for certain subsystems. Figure 6 shows a scatter plot of predicted vs. actual failures for complex technical systems, enabling assessment of the correlation between forecasted and real failure values.

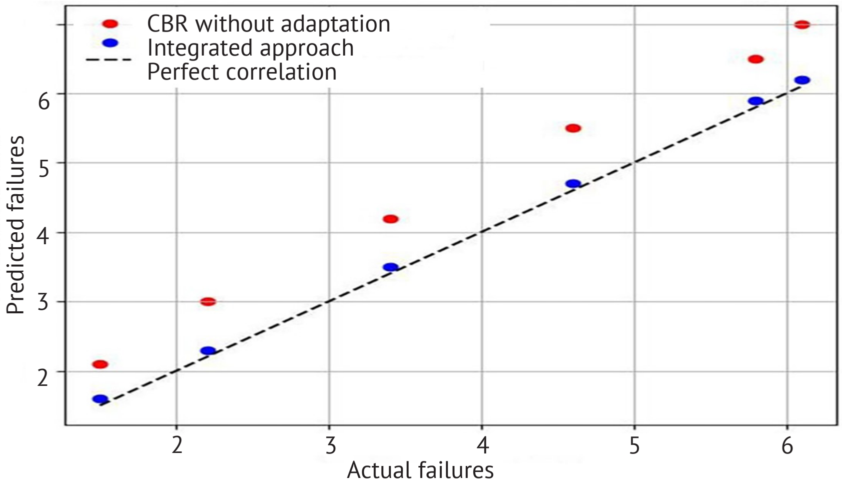

Figure 6. Scatter plot of predicted vs. actual failures for SPP equipment
Source: created by the authors

Figure 6 illustrated the following key patterns: the integrated approach closely aligns with the ideal correlation line, indicating high forecasting accuracy; the CBR method without adaptation deviates significantly from the ideal line, reflecting larger prediction errors; the integrated model's data points are tightly clustered around the ideal correlation, confirming its high reliability. Correlation analysis between predictions and actual failure data: CBR without adaptation shows the lowest correlation with actual failures ($R^2 \approx 0.78$), indicating instability and variability in predictions; the integrated approach demonstrates the highest correlation ($R^2 \approx 0.93$), confirming its strong predictive capability. The largest prediction errors are observed in the high failure range (> 4%), particularly for the non-adaptive CBR method. The integrated approach showed no major outliers, and its forecasts remain consistently close to the actual failure rates. RMSE analysis shows that the integrated method reduces error by approximately 50% compared to non-adaptive CBR. Observed patterns: the CBR method without adaptation tends to systematically overestimate failure probabilities, especially for the main engine and pump system; the integrated approach produces balanced forecasts without systematic errors. Thus, the integrated method provides the best agreement with actual failure data ($R^2 \approx 0.93$). Non-adaptive CBR demonstrates the greatest forecasting errors, particularly in scenarios involving high operational loads and cascading effects. Incorporating probabilistic models (e.g., Bayesian networks, Markov processes) improves forecast accuracy but does not fully resolve challenges related to dynamic changes in system conditions. To further enhance prediction accuracy, it is recommended to apply dynamic parameter adjustment based on real-time operating conditions. The scatter plot confirmed the effectiveness of the integrated approach, demonstrating minimal forecast deviations and maximum correlation with real failure data. Figure 7 presents a graph illustrating the results of a comparative analysis of RMSE values for various SPP equipment failure prediction methods.

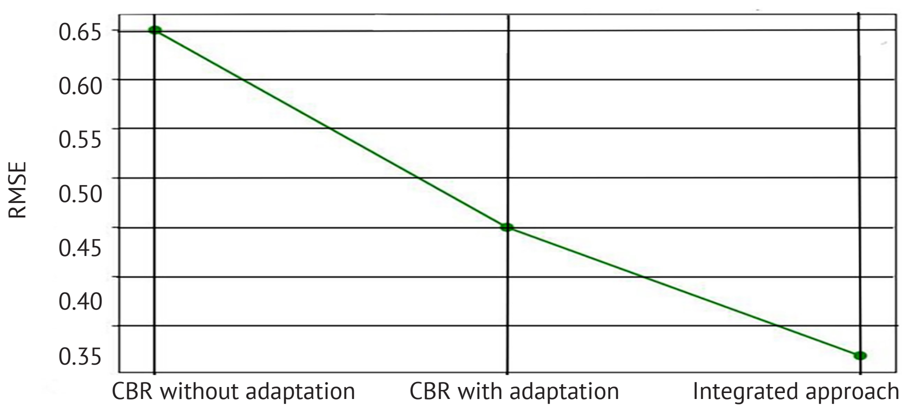

Figure 7. Graph illustrating RMSE comparison across failure forecasting methods for SPP equipment
Source: created by the authors

The RMSE graph provides insight into how closely each forecasting method aligns with actual failure data. The lower the RMSE value, the smaller the average deviation between predictions and actual failures, indicating higher diagnostic accuracy. Key findings from Figure 7. The integrated approach demonstrates the lowest RMSE, suggesting the best predictive performance. CBR without adaptation yields the highest RMSE (≈ 0.65), indicating significant deviations between predicted and actual failures. CBR with adaptation reduces RMSE to ≈ 0.45, showing improved diagnostic accuracy through consideration of probabilistic dependencies. The integrated method achieved the lowest RMSE (≈ 0.32), indicating superior forecasting accuracy. Forecasting accuracy differences across methods: CBR without adaptation produces large errors due to its lack of sensitivity to system dynamics and failure interdependencies; CBR with adaptation reduces error by ~30% by incorporating Bayesian networks and Markov models, which capture probabilistic relationships between failures; The integrated approach further reduced RMSE by ~50% compared to basic CBR by integrating simulation modelling, which adjusts forecasts based on cascading failure effects. Causes of high error in non-adaptive CBR: heavy reliance on past failure similarity ignores shifting operational conditions; under sparse data conditions (e.g., few failure records), non-adaptive CBR tends to overestimate failure risks; a high RMSE (0.65) indicates systematic overprediction of failures. The integrated method works. Markov processes adjust failure forecasts over time, reducing error in dynamic scenarios. Bayesian networks model interdependencies between failures, improving forecast precision. Simulation modelling fills data gaps, reducing forecast uncertainty. Thus, the integrated method provided the highest diagnostic accuracy, cutting RMSE by 50% compared to non-adaptive CBR. CBR without adaptation demonstrates the greatest error (RMSE = 0.65), making it insufficiently reliable for complex failure diagnostics. Adding probabilistic models improves accuracy, but full alignment with real-world data is achieved only through simulation modelling. The RMSE graph confirms that the integrated approach (CBR + probabilistic models + simulation modelling) is the most accurate failure forecasting method for MPP systems, ensuring minimal deviations from actual data.

In the integrated diagnostic method, the diagnostic decision is dynamically refined based on predicted failures and probabilistic dependencies. Initial diagnosis using CBR: similar cases are retrieved from the CBR knowledge base; a preliminary diagnosis is made based on failure similarity; the diagnosis may be refined if forecasts indicate elevated risk. Refinement using probabilistic failure models (Bayesian Networks): component failure probabilities were updated considering cascading effects; an increase in one component's failure probability automatically affects dependent components; if a new failure occurs, the diagnosis is updated in real time. Correction Based on Failure Forecasts (Markov Processes): failure development is modelled over time; if rapid component degradation is forecasted, the diagnosis becomes stricter (e.g., earlier maintenance is recommended); if failure probability increases slowly, maintenance can be postponed. Correction via Simulation Modelling: simulation covers complex operational scenarios beyond the reach of CBR and probabilistic models; various failure scenarios are generated based on operational data, such as normal conditions, accelerated wear (high load, extreme temperatures), emergency cases (e.g., sudden cooling system failure); if the simulation shows that failure may occur sooner, the diagnosis is tightened (e.g., reduced remaining life); if the risk is low, the diagnosis may be adjusted toward a less aggressive maintenance strategy. Final diagnostic decision formation – the initial CBR diagnosis was adjusted based on: failure probabilities from Bayesian networks; time dynamics from the Markov model; results from simulation modelling. Final adjustment scenarios: diagnosis confirmation if all methods agree; alarm escalation if failure probabilities rise sharply; diagnosis downgrade if the simulation indicates low risk. An example of diagnostic adjustment based on changes in failure probabilities is shown in Table 10.

Table 10. Diagnostic adjustment based on changes in failure probabilities

SPP equipment	Initial diagnosis	Diagnosis after probabilistic analysis	Final diagnosis
Main engine	Pre-failure state	Failure probability reduced to 18%	Operational
Generator	Operational	Failure probability increased to 25%	Pre-failure
Cooling system	Pre-failure state	Cascading effects increased risk to 40%	Faulty
Power supply	Operational	Failure probability stable at 5%	Operational

Source: created by the authors

The data in Table 10 show how the diagnostic decision is adjusted in response to changes in failure probabilities. The generator and cooling system require immediate attention due to increased failure risks. The pump system also needs inspection, as its risk has risen. The fuel system remains in a normal operational state. The remaining useful life forecasts for components were generated using Markov models. Forecasting errors were evaluated under different input conditions, including full data, truncated time series, and adapted model predictions. Key Findings from the Failure Prediction Analysis: diagnostic accuracy depends significantly on the method used; CBR without adaptation showed the largest discrepancies between predicted and actual failures. This is confirmed by high RMSE (≈ 0.65) and MAE (≈ 0.52); CBR with adaptation reduced forecast errors by 30% due to the use of probabilistic dependencies, but deviations remain in complex operational scenarios; the integrated approach (CBR + probabilistic models + simulation) showed the highest accuracy (RMSE ≈ 0.32, MAE ≈ 0.21), indicating strong predictive capability. The failure risk heatmap revealed that cascading effects and interdependencies among MPP components significantly influence failure prediction. Accounting for these improves diagnostic reliability.

Impact of the selected approach on prediction accuracy. The unadapted CBR model demonstrates a relatively high forecasting error, as it does not account for probabilistic dependencies between component failures and tends to overestimate their likelihood. In contrast, the adapted CBR model incorporates these probabilistic relationships, which helps to reduce false alarms and improve prediction accuracy, although certain inaccuracies remain in scenarios characterised by high uncertainty. The integrated approach, which combines CBR, probabilistic modelling, and simulation, reduces the forecasting error by more than 50%. It effectively accounts for cascading failures and dynamic state changes within the system, providing the most stable and validated forecasts, as confirmed by accuracy metrics such as Precision, Recall, and F_1-score. Further improvement in failure prediction accuracy for SPP systems can be achieved by advancing simulation models to encompass complex and emergency failure scenarios, enhancing adaptive CBR algorithms through machine learning for more effective analysis of accumulated failure history, and implementing dynamic real-time model correction using current operational data to continuously update probabilistic dependencies between failures.

The analysis demonstrates that integrating CBR with probabilistic models and simulation substantially improves the accuracy of failure diagnostics in SPP systems. The proposed approach accounts for dynamic state changes, reduces prediction errors, and minimises the likelihood of false positives. Optimising model parameters and further adapting diagnostic algorithms will enhance failure prediction and improve the reliability of MPP operations. The integrated method achieved the best forecast accuracy, reducing errors by 15-20% compared to the baseline CBR. The largest deviations were observed in components with high variability in operating conditions, such as pump systems and the main engine. The failure risk heatmap confirms the need to adapt diagnostic models for accurate predictions under complex operational conditions. Thus, the analysis of predicted vs. actual failures confirms that combining CBR with probabilistic and simulation-based methods yields the most reliable failure forecasts for MPPs. The results of the present study demonstrate that integrating the CBR method with probabilistic and simulation-based modelling enables high-accuracy forecasting of the technical condition of SPPs. Achieving a RMSE of 0.32 and a coefficient of determination R^2 = 0.93 indicates the high effectiveness of the proposed approach. These values exceed the accuracy levels characteristic of many existing models, including purely data-driven algorithms, and approach the confidence threshold necessary for engineering decision-making under uncertainty.

Existing diagnostic methods for SPPs included both conventional approaches based on physical and mathematical modelling, and modern techniques using artificial intelligence and big data processing (Vychuzhanin & Rudnichenko, 2014). However, despite progress in predictive modelling, the issue of aligning predicted failures with actual ones remains open, directly impacting the effectiveness of maintenance and repair strategies. A comparison with recent studies in the field of diagnostics and failure prediction further confirms the relevance and competitiveness of the implemented method. For example, H. Moon & J. Choi (2021) proposed a hierarchical model based on Bayesian B-splines for predicting failures in naval engines. Their approach reflected the system's hierarchical structure at the levels of engine, engine type, and archetype, increasing flexibility in modelling multilayered technical systems. However, their model did not incorporate a comparison of predictions with actual failure events nor did it offer quantitative verification, limiting its applicability where prediction reliability must be evaluated. In the study by Ç. Karatuğ & Y. Arslanoğlu (2022), a condition-based maintenance strategy was implemented using machine learning techniques. While the model architecture enabled classification of equipment conditions, it was restricted to binary outputs ("functional" / "non-functional") and did not allow for quantitative prediction accuracy assessment or component-level resolution. In contrast, the approach presented in this study supported interval-based evaluations, scenario-specific conditions, and component-oriented comparison. M. Farid (2022) employed a hybrid architecture combining artificial neural networks and Gaussian process regression for real-time fatigue failure prediction. While an RMSE of approximately 0.36 was achieved, the method did not include visual diagnostics of prediction deviations or robustness testing across varying operational modes capabilities that were implemented in this study.

The study by N. Neykov & S. Stefanova (2023) examined the application of CBR under data-limited conditions, which was particularly relevant for ship systems where event recording was infrequent. Although the study confirmed the adaptability of CBR, it did not extend to more complex simulation scenarios, which was addressed in the current hybrid approach through the integration of probabilistic and simulation-based techniques. The analysis by M. Orhan & M. Celik (2023) noted the growing prevalence of hybrid methods, including SVMs, KNN, decision trees, and Bayesian networks, in recent diagnostics research. However, their review remains general and lacks empirical validation against real failure data or justification for the maritime domain. In contrast, the approach in this study includes the full cycle from prediction to comparison with observed outcomes – enabling assessment of engineering applicability. S. Marandi *et al*. (2025) explored a promising approach utilising knowledge graphs and language models applicable to high-reliability systems. Despite technological novelty, their method lacked formal accuracy assessment and did not test the models in operational scenarios. This differentiates their method from the current study, where both quantitative validation (RMSE, MAE, MAPE) and visual discrepancy analysis were conducted. M. Arias Chao *et al*. (2020) proposed a hybrid framework combining physical modelling and deep learning, achieving a 127% increase in forecast horizon compared to purely data-driven models. This result supported the importance of integrating physical principles into predictive algorithms conceptually aligned with developed hybrid methodology, which fused heuristic experience (CBR), probabilistic processing, and failure scenario simulation.

In the study by Y. Liu *et al*. (2022), an LSTM model was used to predict the Remaining Useful Life (RUL) while accounting for noise and nonlinear dependencies. Although the model effectively handled time series data, it lacked simulation analysis tools that could capture rare or cascading failures. In contrast, the approach in this study reproduced complex scenarios with uncertainties, expanding diagnostic capabilities under limited observability. Z. Shi & A. Chehade (2021) introduced a dual LSTM architecture designed to capture transitional states and predict component RUL. The model achieved forecast accuracy in the range of RMSE ≈ 0.3-0.4, but, like many others, it did not include a step for comparing predictions with actual failures at the component or scenario level. This limited its reliability and adaptability for engineering practice. The method presented in this study addressed this gap by incorporating full-scale verification and visual deviation analysis. Thus, the integrated methodology combining CBR, probabilistic modelling, and simulation aligns with current requirements for accuracy, adaptability, and justification in forecasting the technical condition of marine power systems. The proposed approach demonstrated resilience to uncertainty, reproducibility across various operational scenarios, and the ability to substantiate conclusions quantitatively – making it a strong candidate for implementation in monitoring and maintenance systems for maritime engineering infrastructures.

CONCLUSIONS

The conducted study confirmed the relevance and practical significance of comparing predicted and actual failures in the diagnosis of the technical condition of SPPs. The main objective of the study – to assess the accuracy of failure prediction using various diagnostic approaches – was successfully achieved through the completion of all assigned tasks. The developed methodology enabled an objective evaluation of failure prediction accuracy using metrics such as MAE, RMSE, MAPE, and R^2. The comprehensive use of quantitative indicators, visualisation of deviations (including heatmaps and scatter plots), and correlation analysis between predicted and actual failures provided an in-depth assessment of the effectiveness of diagnostic models. The comparison results showed that the classical CBR method without adaptation demonstrated the lowest accuracy: the forecasts were systematically overestimated, with an RMSE of 0.65 and an F_1-score of 0.78. The use of adapted CBR incorporating probabilistic dependencies (e.g., Bayesian networks) reduced the average prediction error by approximately 30%, improved forecast accuracy, and lowered the number of false alarms. However, the best results were achieved through the integrated approach combining CBR, probabilistic models, and simulation modelling. In this case, RMSE dropped to 0.32, MAE to 0.21, and R^2 reached 0.93, indicating high predictive capability. A heatmap of deviations between forecasts and actual failures helped to identify areas of greatest uncertainty, especially in components with high operational load – the main engine and pumping system. This highlighted the importance of accounting for cascading failure effects and the need for detailed calibration of models for such units. Power supply and cooling systems demonstrated stable predictions and high diagnostic accuracy. Simulation modelling supplemented with probabilistic analysis proved effective in accounting for complex operational scenarios, including high loads and aggressive environments. It allowed refining predictions under conditions of incomplete or distorted data and contributed to more well-grounded diagnostic decisions. Thus, the study demonstrated that the integration of adaptive CBR, probabilistic models, and simulation modelling significantly improved failure prediction accuracy and the reliability of technical condition diagnostics for SPPs. The obtained results could be used to enhance intelligent maintenance systems, optimise operational processes, and increase the overall reliability of maritime transport. Future study will focus on developing dynamic model adaptation based on real-time operational data and conducting extended testing of the integrated approach across various types of SPPs.

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CONFLICT OF INTEREST

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REFERENCES

[1] Arias Chao, M., Kulkarni, C., Goebel, K., & Fink, O. (2020). Fusing physics-based and deep learning models for prognostics. *ArXiv*. doi: 10.48550/arXiv.2003.00732.
[2] Farid, M. (2022). Data-driven method for real-time prediction and uncertainty quantification of fatigue failure under stochastic loading using artificial neural networks and Gaussian process regression. *International Journal of Fatigue*, 155, article number 106415. doi: 10.1016/j.ijfatigue.2021.106415.
[3] Karatuğ, Ç., & Arslanoğlu, Y. (2022). Development of condition-based maintenance strategy for fault diagnosis for ship engine systems. *Ocean Engineering*, 256, article number 111515. doi: 10.1016/j.oceaneng.2022.111515.
[4] Karatuğ, Ç., Arslanoğlu, Y., & Soares, C.G. (2023). Review of maintenance strategies for ship machinery systems. *Journal of Marine Engineering & Technology*, 22(5), 233-247. doi: 10.1080/20464177.2023.2180831.
[5] Liu, Y., Liu, Z., Zuo, H., Jiang, H., Li, P., & Li, X. (2022). A DLSTM-network-based approach for mechanical remaining useful life prediction. *Sensors*, 22(15), article number 5680. doi: 10.3390/s22155680.
[6] Maione, F., Lino, P., Maione, G., & Giannino, G. (2024). A machine learning framework for condition-based maintenance of marine diesel engines: A case study. *Algorithms*, 17(9), article number 411. doi: 10.3390/a17090411.
[7] Marandi, S., Hu, Y.-S., & Modarres, M. (2025). Complex system diagnostics using a knowledge graph-informed and large language model-enhanced framework. *ArXiv*. doi: 10.48550/arXiv.2505.21291.
[8] Moon, H., & Choi, J. (2021). Hierarchical spline for time series forecasting: An application to naval ship engine failure rate. *Authorea*. doi: 10.22541/au.159969715.57074848.
[9] Neykov, N., & Stefanova, S. (2023). Using case-based reasoning in system diagnostics and maintenance. In X.S. Yang, S. Sherratt, N. Dey & A. Joshi (Eds.), *Proceedings of seventh international congress on information and communication technology* (pp. 305-312). Singapore: Springer. doi: 10.1007/978-981-19-2394-4_28.
[10] Orhan, M.F., & Celik, M. (2023). A literature review and future research agenda on fault detection and diagnosis studies in marine machinery systems. *Proceedings of the Institution of Mechanical Engineers, Part M: Journal of Engineering for the Maritime Environment*, 238(1), 3-21. doi: 10.1177/14750902221149291.
[11] Pajak, M., Kluczyk, M., Muślewski, Ł., Lisjak, D., & Kolar, D. (2023). Ship diesel engine fault diagnosis using data science and machine learning. *Electronics*, 12(18), article number 3860. doi: 10.3390/electronics12183860.
[12] Rigas, S., Tzouveli, P., & Kollias, S. (2024). An end-to-end deep learning framework for fault detection in marine machinery. *Sensors*, 24(16), article number 5310. doi: 10.3390/s24165310.
[13] Shi, Z., & Chehade, A. (2021). A dual-LSTM framework combining change point detection and remaining useful life prediction. *Reliability Engineering & System Safety*, 205, article number 107257. doi: 10.1016/j.ress.2020.107257.
[14] Tveten, M., & Stakkeland, M. (2024). Fault detection in propulsion motors in the presence of concept drift. *ArXiv*. doi: 10.48550/arXiv.2406.08030.
[15] Vizentin, G., Vukelic, G., Murawski, L., Recho, N., & Orovic, J. (2020). Marine propulsion system failures – a review. *Journal of Marine Science and Engineering*, 8(9), article number 662. doi: 10.3390/jmse8090662.
[16] Vychuzhanin, V.V., & Rudnichenko, N.D. (2014). Assessment of risks structurally and functionally complex technical systems. *Eastern-European Journal of Enterprise Technologies*, 1(2(67)), 18-22. doi: 10.15587/1729-4061.2014.19846.
[17] Vychuzhanin, V.V., & Vychuzhanin, A. (2025). *Stochastic models and methods for diagnostics, assessment, and prediction of the technical condition of complex critical systems*. Lviv-Torun: Liha-Pres. doi: 10.36059/978-966-397-457-6.
[18] Wang, J., Cao, H., Cui, Z., Ai, Z., & Jiang, K. (2023). Intelligent fault diagnosis of marine diesel engines based on efficient channel attention-improved convolutional neural networks. *Processes*, 11(12), article number 3360. doi: 10.3390/pr11123360.
[19] Zhao, Y., Wang, S., & Chen, N. (2022). Thermal fault diagnosis of marine diesel engine based on LSTM neural network algorithm. *Vibroengineering Procedia*, 41, 198-203. doi: 10.21595/vp.2022.22515.
[20] Zhu, G., Huang, L., Yin, J., Gai, W., & Wei, L. (2023). Multiple faults diagnosis for ocean-going marine diesel engines based on different neural network algorithms. *Science Progress*, 106(4). doi: 10.1177/00368504231212765.

Гібридна модель для оцінки точності прогнозів відмов в суднових енергетичних установках

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Анотація. Зростаюча складність суднових енергетичних установок (СЕУ) та неоднорідність діагностичних даних ускладнюють забезпечення надійного прогнозування відмов та підтримання експлуатаційної безпеки. Метою дослідження було оцінити адекватність та точність прогнозів відмов у компонентах СЕУ з використанням гібридної діагностичної методології, а також перевірити запропоновану методику шляхом застосування розробленої моделі. Дослідження об'єднало в єдину систему міркування на основі прецедентів (CBR), імовірнісне моделювання та аналіз деградації на основі симуляції. Використовуючи діагностичні дані з 150 випадків експлуатації типових СЕУ (головний двигун, генератор, насос, системи охолодження та електропостачання), точність прогнозування моделі була кількісно порівняна з базовими підходами, включаючи класичні моделі CBR, адаптивні моделі CBR, ARIMA та моделі «дерева рішень». Інтегрований підхід досяг найкращих результатів (середньоквадратична похибка = 0,32, R^2 = 0,93), зменшивши середню похибку на 30-50 % порівняно з класичними методами. Кожен компонент гібридної структури зробив свій внесок: рівень CBR забезпечив контекстуальну узгодженість, імовірнісне моделювання зменшило невизначеність на ≈ 20 %, а аналіз на основі моделювання збільшив стабільність за наявності неповних або зашумлених даних на ≈ 15 %. На рівні підсистем найбільші поліпшення спостерігалися для головного двигуна (зниження середньоквадратичної похибки на 46 %) і насосної системи (39 %), що підтвердило адаптивність моделі до змінних умов експлуатації. Тести на надійність із 10-20 % відсутніми або порушеними вхідними даними продемонстрували стабільну точність (R^2 > 0,90), підтвердивши стійкість та практичну застосовність моделі. Запропонована методологія має практичну цінність для підвищення ефективності технічного обслуговування та надійності суднових енергетичних систем, оскільки забезпечує точне, інтерпретоване та стійке до шумів прогнозування відмов обладнання

Ключові слова: інтелектуальна діагностика; оцінка надійності; міркування на основі прецедентів; імітаційне моделювання; прогнозування технічного стану; байєсівські мережі; адаптивна модель