ТЕХНІЧНІ НАУКИ

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ADAPTIVE CASE-BASED REASONING WITH PROBABILISTIC INTEGRATION FOR THE DIAGNOSIS AND PROGNOSIS OF THE TECHNICAL CONDITION OF COMPLEX SYSTEMS

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АДАПТИВНЕ ПРЕЦЕДЕНТНЕ МІРКУВАННЯ З ІМОВІРНІСНОЮ ІНТЕГРАЦІЄЮ ДЛЯ ДІАГНОСТИКИ ТА ПРОГНОЗУВАННЯ ТЕХНІЧНОГО СТАНУ СКЛАДНИХ СИСТЕМ

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This study introduces an advanced adaptive Case-Based Reasoning (CBR) framework designed for real-time diagnosis and prognosis of the technical condition of ship power plants, achieved through the seamless integration of Bayesian networks, Markov process modeling, and cognitive simulation within a dynamically adaptive environment. Traditional CBR approaches, while effective at retrieving analogues from historical case archives, often lack the capability to capture complex stochastic dependencies among system components, dynamic degradation patterns under varying operational loads, and real-time contextual variations in sensor data. To address these limitations, the proposed methodology incorporates six integrated phases: data acquisition and normalization, ensuring consistent standardization of heterogeneous sensor readings and operational parameters; probabilistic failure analysis utilizing Bayesian networks to compute conditional failure probabilities and adjust case relevance weights in light of intercomponent dependencies; scenario-driven forecasting based on discrete-time Markov process models to simulate state transition dynamics and predict degradation trajectories; decision adaptation and fusion, which combines classical CBR retrieval outcomes, probabilistic inference results, and forecasted degradation estimates via dynamically normalized weighted coefficients (α, β, γ) that reflect current risk levels; knowledge base maintenance through the incorporation of newly acquired real cases and synthetically generated cases from cognitive simulation, thus enhancing retrieval accuracy and mitigating data scarcity; and automated generation of preventive maintenance recommendations aligned with predicted remaining useful life. Validation experiments conducted on a comprehensive dataset of more than 11 000 historical and synthetic cases demonstrated a diagnostic accuracy of 91 % compared to 79 % achieved by traditional CBR, a 6.7 % reduction in false alarms, a 5–7 % improvement in remaining useful life prediction accuracy, and a 4.7 % decrease in forecast error attributable to the cognitive simulation module, which also improved rare-failure detection rates by 5.1 %. These empirical results confirm the proposed system's high reliability and robustness under fluctuating operational loads and cascading failure scenarios, as well as its seamless integration into onboard monitoring architectures for optimized maintenance scheduling, reduced unplanned downtime, and enhanced operational safety of maritime power plants.

Keywords: *probabilistic analysis, Bayesian networks, Markov processes, cognitive models, dynamic adaptation, technical diagnostics, expert systems*

Introduction. Modern technical condition monitoring systems for complex systems, particularly SPPs, face a number of challenges due to increasing equipment complexity, the rapid growth of operational data volumes, and the need for failure prognosis over time [1]. Traditional CBR methods, which focus primarily on retrieving similar historical cases, are limited in their ability to account for the stochastic nature of failure development and the dynamic evolution of the TC of CTSs. This limitation results in reduced diagnostic accuracy under uncertainty and variable operational loads. Under variable loads and complex cascading interactions between subsystems, this leads to lower diagnostic and prognostic reliability and increases the risk of incorrect decisions.

To enhance diagnostic performance, a methodology for adapting CBR-based decisions has been developed that integrates three key components. Bayesian networks model probabilistic dependencies between component failures and account for cascading effects in fault development. Markov processes forecast changes in equipment condition over time by describing probabilistic transitions between operational and failed states. Simulation modeling dynamically updates weighting coefficients in the CBR model based on real operational data and synthesizes new cases for underrepresented failure scenarios. The joint use of these approaches enables more accurate estimation of failure probabilities for critical SPP components under current operating conditions, correction of CBR-based decisions based on predicted changes in technical condition, automatic adaptation of the case base and real-time reallocation of parameter importance, and generation of substantiated preventive maintenance recommendations to extend equipment life.

The need to develop adaptive CBR mechanisms is confirmed by a review of recent studies in the field. For instance, Nikpour and Aamodt [2] proposed the integration of Bayesian networks into CBR for diagnosing failures under uncertainty, improving decision accuracy. However, their approach relies on static network structures and lacks dynamic adaptation to changing operational parameters. Similar limitations are noted in the work of [3], who applied the Shapley Attitude Integral to account for attribute interactions and expert preferences in case retrieval, significantly improving search quality. However, their method does not address the adaptation of decisions based on probabilistic prognosis of system state. Schultheis [4] presents a hybrid TCBR approach combining CBR with transformers to adapt time series in predictive maintenance tasks, offering enhanced explainability. Nevertheless, the proposed model depends on the presence of similar time series in the database and lacks quantitative uncertainty estimation of forecasts. In their review of explainable CBR, Schoenborn et al. [5] outlined key goals for decision explanation but noted insufficient integration of explainability with probabilistic methods for equipment longevity prediction. Kumar et al. [6] considered inter-case dependencies in process-oriented CBR, improving retrieval accuracy, but did not address the temporal evolution of cases or failure forecasting. Expanding similarity measures, Malburg et al. [7] proposed attribute weight correction when sensor data is missing, enhancing retrieval robustness, but their method does not implement dynamic adaptation of decisions. Additionally, Gould et al. [8] proposed an AA-CBR-P argumentation mechanism incorporating user preferences in case comparison. However, this method does not account for dynamic changes in equipment condition or probabilistic failure forecasting. In their review on Real-Time Fault Diagnosis methods, Yan et al. [9] emphasized the importance of applying CBR for online diagnostics in industrial systems, while also highlighting the insufficient development of case adaptation mechanisms based on failure prognosis. Thus, existing research addresses isolated aspects of improving CBR quality, but in most cases does not provide a comprehensive solution for dynamic decision adaptation based on probabilistic forecasting of equipment technical condition. This underscores the relevance of the present study.

The aim of this paper is to develop and experimentally validate an adaptive CBR mechanism for diagnosing ship power plants. The proposed approach integrates probabilistic failure analysis using Bayesian networks, time-based forecasting of component technical condition via Markov processes, and dynamic updating of parameter weighting through simulation modeling. The implementation of the proposed approach will improve diagnostic accuracy, take into account the dynamic evolution of equipment condition, and provide effective preventive maintenance recommendations for extending the service life of ship power plants.

Results. Traditional CBR systems are based on retrieving similar failures from a case base and applying solutions derived from past operational experience [1, 10]. However, this approach has a number of significant limitations: neglect of component condition dynamics (classical systems do not account for the gradual degradation of equipment under operational stress); lack of consideration for external operational factors affecting the probability of failure progression; insufficient modeling of cascading failure effects, where interrelated component failures lead to systemic disruptions that are not reflected in diagnostic decision-making.

Integrating CBR with probabilistic methods and simulation modeling helps to overcome these limitations through: refinement of component condition assessments based on modeling probabilistic dependencies between them (using Bayesian networks); forecasting of failure progression over time using Markov process models; and dynamic updating of the case base through simulation of new scenarios and incorporation of actual operational data.

Some key interdependencies between failures of SPP components and their impact on system functionality are presented in Table 1.

Table 1

Interdependencies of SPP Component Failures and Their Impact on the System

Equipment	Dependent Elements	System Impact
Generator	Electrical network	Power reduction
Pump	Cooling system	Overheating
Engine	Power transmission	Loss of thrust

From the table, it follows that the failure of individual equipment may initiate cascading processes that critically affect the overall operability of the SPP. For example, a generator power drop disrupts power supply to consumers, while pump failure leads to overheating of key systems.To formalize the adaptive CBR decision correction mechanism based on probabilistic analysis, we introduce the basic dependencies.

Let: p_i – the predicted probability of failure for equipment i based on a Bayesian network; s_i – the initial similarity measure of the current case with the i-th precedent; w_i – the adaptive weight of the precedent.

The adaptive weight of the precedent is defined by the formula:

$$\omega_i = s_i \cdot (1 - p_i), \quad (1)$$

where the correction factor ($1-p_i$) reduces the precedent's weight with an increased failure risk, thereby improving diagnostic robustness under degrading conditions.

The forecast of equipment technical condition over time is carried out using an exponential degradation model of operability probability:

$$P_{working}(t) = P_{working}(0) \cdot e^{-\lambda t}, \quad (2)$$

where: λ – the failure rate of the component (a parameter dependent on operational conditions and equipment characteristics).

The final diagnostic decision D_{final} is formed based on the aggregation of classical CBR decision, probabilistic analysis, and condition forecasting:

$$D_{final} = \alpha \cdot D_{CBR} + \beta \cdot D_{Bayes} + \gamma \cdot D_{Sim}, \quad (3)$$

where $\alpha,\beta,\gamma \geq 0$ are normalized weight coefficients satisfying the condition $\alpha+\beta+\gamma=1$.

Thus, CBR decision adaptation includes adjustment of initial conclusions based on probabilistic equipment states, prediction of technical condition changes, and case base updates considering new operational data from complex technical systems. This approach significantly increases the accuracy of diagnostics and reliability of SPP functioning under dynamic operating conditions.

The adaptive CBR mechanism for SPP diagnostics is implemented as an algorithm consisting of six main stages: data collection and preprocessing, failure probability correction, simulation modeling, final diagnosis formation, case base update, and maintenance recommendation generation.

Input data:

array of operational parameters of the SPP: $X = \{x_1, x_2, \ldots, x_m\}$;

CBR case base: $\{(C_j, s_j)\}_{j=1}^{N}$, where s_j is the similarity measure of the case.

Output data: final diagnosis D_{final}; updated case base considering new cases and recalculated weights.

CBR decision adaptation includes the following stages:

Stage 1. Data collection and preprocessing.

At this stage, the parameters of the SPP equipment condition are collected and prepared for further processing: reading of input parameters X; feature normalization (min–max or Z-score) to ensure comparability of values and increase computational stability;

Stage 2. Failure probability correction**.**

This stage accounts for operational factors and probabilistic dependencies between failures:

for each component, the posterior probability of failure is calculated using a Bayesian network:

$$p_i = P(failure_i | X);$$

the weights of the cases are corrected based on probabilistic analysis (1), which improves the relevance of similar case retrieval;

Stage 3. Simulation modeling.

To forecast the development of the technical system, simulation modeling is applied: generation of K SPP operation scenarios; for each scenario, simulation of component state evolution over time using the Markov model (2); evaluation of dynamic inference D_{Sim}based on failure probabilities across all scenarios;

Stage 4. Formation of the final diagnosis.

The final diagnostic decision is formed based on the integration of various sources of information: calculation of the base diagnosis D_{CBR} using the adjusted case weights w_i; aggregation of CBR, Bayesian analysis, and simulation modeling inferences (3). The optimal solution is selected as the adjusted diagnostic decision;

Stage 5. Case base update.

The system updates the knowledge base based on new data and diagnostic results: addition of new cases arising during operation; recalculation of diagnostic accuracy metrics (Accuracy, Precision, Recall, F1-score) to evaluate adaptation effectiveness; if necessary, adjustment of global weighting coefficients α, β, γ controlling the contribution of each method;

Stage 6. Maintenance recommendation generation. Based on the formed diagnosis and the predicted equipment state, maintenance recommendations are developed to extend the SPP's service life and prevent the development of critical failures.

Figure 1 illustrates the process of adapting CBR decisions considering failure probabilistic analysis.

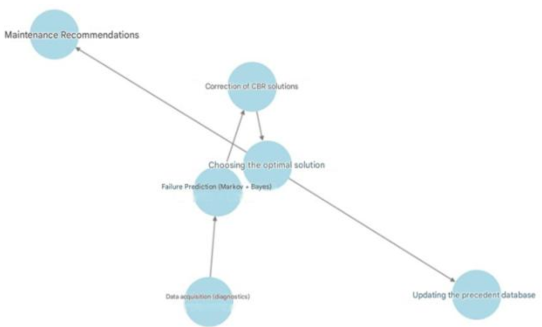

Fig. 1. Adaptation of CBR Decisions Considering Probabilistic Analysis of SPP Equipment Failures

The diagram illustrates the general concept of adaptation: input data → forecasting → decision correction → recommendations. A step-by-step flowchart of the adaptive CBR mechanism implementation is shown in Figure 2. It details the stages of equipment condition diagnostics and forecasting based on the integration of CBR methods, Bayesian analysis, and simulation modeling.

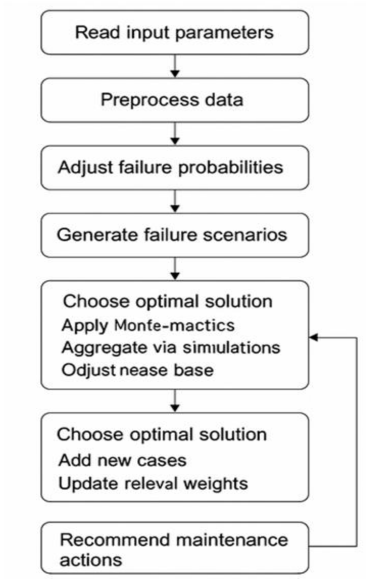

Fig. 2. Flowchart of the Adaptive CBR Algorithm for SPP Diagnostics

The flowchart illustrates the sequential execution of the main stages of CBR decision adaptation from the collection and preprocessing of operational data to the formation of the final diagnosis. A key feature of the algorithm is the branching after the aggregated inference: based on the diagnosis, maintenance recommendations are simultaneously generated, and the case base is updated to improve the accuracy of future diagnostic decisions.

Key features of the adaptive mechanism include: assessment of case relevance: standard retrieval of similar cases is complemented by probabilistic analysis of component states, allowing the selection of safer scenarios in cases of forecasted failure risk; correction of diagnostic decisions: when new data is received, the system automatically refines the diagnosis, suggesting preventive or repair actions if risk thresholds are exceeded; automatic learning on new data: the case base is dynamically updated, and model weights are adjusted based on analysis of operational information and forecasting results.

Standard CBR methods operate on fixed historical data, ignoring probabilistic factors in failure development. The integration of Bayesian networks and Markov models transforms CBR into a dynamically adaptive system capable of accounting for both the current and predicted equipment states, thereby increasing diagnostic accuracy and extending the life cycle of critical technical systems.

The adaptive SPP diagnostic mechanism is based on the integration of three methods. CBR, probabilistic failure analysis (Bayesian networks), and simulation modeling based on Markov processes. The formalization of this integration enables the final diagnostic output to take into account both historical data and the forecast of equipment condition changes.

The final diagnosis D_{final} is defined as a function of three components:

$$D_{final} = f\left(D_{CBR}, D_{Bayes}, D_{Sim}\right),$$

where *f(·)* is the function defining the integration mechanism of the decisions;

D_{CBR}: diagnosis based on precedents, determined by the similarity function between the current case and historical ones; includes the diagnosis and its associated error from the CBR method;

D_{Bayes}: probabilistic diagnosis based on Bayesian networks, taking into account the interdependence of component failures; includes correction based on failure probability models and associated error;

D_{Sim}: diagnosis based on simulation modeling, forecasting the system's behavior over time; includes adjustments from the cognitive simulation model and its related error;

D_{final}: the final diagnostic output combining all three methods.

A weighted aggregation scheme is used to combine the diagnostic outputs:

$$D_{final} = \alpha_d \cdot D_{CBR} + \beta_d \cdot D_{Bayes} + \gamma_d \cdot D_{Sim}$$

where $\alpha_d, \beta_d, \gamma_d$ are weighting coefficients reflecting the contribution of each method. These coefficients satisfy the normalization condition: $\alpha_{d+}\beta_d + \gamma_d = 1$

The weight β_d increases if the failure probability from the Bayesian network exceeds a threshold value. The weight γ_d increases if the simulation models reveal a high risk of failure, even if CBR finds no similar cases.

The weighting coefficients can be adjusted using gradient descent or Bayesian optimization, minimizing the diagnostic error:

$$\omega^* = arg\,min_{\alpha,\beta,\gamma} \sum_{i=1}^{N} (D_{true,i} - D_{final,i})^2$$

Similarly – Definition of weight coefficients.

The weight coefficients $\alpha_d, \beta_d, \gamma_d$ can be determined by various methods depending on the available data and the problem formulation.

1. Determining weight coefficients based on diagnostic error

If the average diagnostic errors E_{CBR}, E_{Bayes}, E_{Sim} are known, the weights can be set as follows:

$$\alpha_d = \frac{1/E_{CBR}}{1/E_{CBR} + 1/E_{Bayes} + 1/E_{Sim}};$$

$$\beta_d = \frac{1/E_{Bayes}}{1/E_{CBR} + 1/E_{Bayes} + 1/E_{Sim}};$$

$$\gamma_d = \frac{1/E_{Sim}}{1/E_{CBR} + 1/E_{Bayes} + 1/E_{Sim}}$$

2. Determining weight coefficients based on confidence coefficients

If for each diagnostic method the confidence level $C_{CBR}, C_{Bayes}, C_{Sim}$ is known, the weights can be calculated as follows:

$$\alpha_d = \frac{C_{CBR}}{C_{CBR} + C_{Bayes} + C_{Sim}};$$

$$\beta_d = \frac{C_{Bayes}}{C_{CBR} + C_{Bayes} + C_{Sim}}$$

$$\gamma_d = \frac{C_{Sim}}{C_{CBR} + C_{Bayes} + C_{Sim}}$$

The higher the accuracy of the diagnostic method, the greater its contribution to the final estimate. The confidence coefficients $C_{CBR}, C_{Bayes}, C_{Sim}$ can be determined based on previous diagnostic data, for example, as the proportion of correctly identified failures by this method.

3. Determining weight coefficients based on diagnostic accuracy

If the accuracies of diagnostic methods are known (e.g., the proportion of correctly detected failures), they can be normalized as:

$$\alpha_d = \frac{P_{CBR}}{P_{CBR} + P_{Bayes} + P_{Sim}};$$

$$\beta_d = \frac{P_{Bayes}}{P_{CBR} + P_{Bayes} + P_{Sim}};$$

$$\gamma_d = \frac{P_{Sim}}{P_{CBR} + P_{Bayes} + P_{Sim}}$$

Dynamic weight update.

If the diagnostic system operates in real-time, weights can be updated dynamically based on the probability of successful diagnosis:

$$\alpha_d(t+1) = \alpha_d(t) + k\big(P_{CBR} - P_{final}\big);$$
$$\beta_d(t+1) = \beta_d(t) + k\big(P_{Bayes} - P_{final}\big);$$
$$\gamma_d(t+1) = \gamma_d(t) + k\big(P_{Sim} - P_{final}\big),$$

where P_{CBR}, P_{Bayes}, P_{Sim} – predicted probabilities of correct diagnosis;

k – adaptation rate coefficient.

If there is no data on method quality, weights can be set uniformly:

$$\alpha_{d+}\beta_d + \gamma_d = \frac{1}{3}$$

Proportional distribution based on method accuracy.

If the relative accuracies of CBR (P_{CBR}), probabilistic models (P_{Bayes}), and simulation modeling (P_{Sim}) are known, then α_d, β_d and γ_d are normalized as follows:

$$\alpha_d = \frac{P_{CBR}}{P_{CBR} + P_{Sim}} \cdot (1 - \gamma_d):$$

$$\beta_d = \frac{P_{Bayes}}{P_{Bayes} + P_{Sim}} \cdot (1 - \alpha_d);$$

$$\gamma_d = \frac{P_{Sim}}{P_{Bayes} + P_{Sim}} \cdot (1 - \alpha_d)$$

Definition of $\boldsymbol{\alpha_d}$, $\boldsymbol{\beta_d}$ and $\boldsymbol{\gamma_d}$ through inverse errors (the smaller the error, the higher the contribution).

If the average model errors $E_{CBR,}$ E_{Bayes} and E_{Sim} are known, the distribution is set as:

$$\alpha_d = \frac{1/E_{CBR}}{1/E_{CBR} + 1/E_{Sim}} \cdot (1 - \gamma_d);$$

$$\beta_d = \frac{1/E_{Bayes}}{1/E_{Bayes} + 1/E_{Sim}} \cdot (1 - \alpha_d);$$

$$\gamma_d = \frac{1/E_{Sim}}{1/E_{Bayes} + 1/E_{Sim}} \cdot (1 - \alpha_d)$$

If no additional information is available, weight coefficients β_d and γ_d are divided equally:

$$\beta_d = \gamma_d = \frac{1 - \alpha_d}{2}$$

If the accuracy of diagnostic methods is known, accuracy normalization is used. If errors are known, inverse error normalization is used. If there is no data, uniform distribution is applied. If a method shows higher accuracy on current data, its weight increases. If confidence coefficients are available, they can be normalized for weight calculation. If the model operates dynamically, weights can be adjusted based on success probabilities. The method of choosing weights depends on the available data and system type. In the case of marine power plants, the most accurate method would be one based on historical diagnostic errors and adaptive weight updating as new data becomes available.

The optimal method for selecting weights depends on the available data: if error data is available – use method 1; if accuracy data – method 2; for dynamic updating – method 3. Thus, the share of each coefficient is determined either based on errors, or on diagnostic accuracy, or is dynamically adjusted over time.

Diagnosis based on CBR.

The CBR method assesses the similarity of a new failure *X* with known cases C_i in the database. The diagnosis based on case retrieval:

$$D_{CBR}(X) = \sum_{i=1}^{N} \omega_i \cdot S(X, C_i) \cdot D_i$$

where $S(X, C_i)$ – similarity measure between the current case *X* and precedent C_i;

D_i – diagnostic result for the i-th precedent;

ω_i – reliability weight of the precedent.

Bayesian diagnosis.

Diagnostic inference based on probabilistic dependencies:

$$D_{Bayes} = \sum_{k=1}^{K} P(C_k| E) \cdot D_k$$

The probability of component C_k failure, considering dependencies in the system, is set by Bayes' formula:

$$P(C_k|E) = \frac{P(E|C_k) \cdot P(C_k)}{\sum_j P(E|C_j) \cdot P(C_j)}$$

where $P(C_k)$– prior probability of C_k failure;

$P(E|C_k)$– likelihood of observed data given failure of C_k.

Simulation modeling

Simulation modeling predicts the probability of failure over time.

The probability of component C_k being in a certain state at time t is determined by the Markov model:

$$P(C_k, t+1) = P(C_k, t) \cdot P_{trans}$$

where P_{trans}– transition probability matrix

Predicted failure probability after t hours:

$$D_{Sim}(t) = 1 - P(C_k, t),$$

where $P(C_k, t)$ – probability calculated via the Markov process transition matrix.

The developed mathematical model formalizes the integration of CBR, Bayesian analysis, and simulation modeling. The final diagnostic output D_{final} accounts for both historical data and probabilistic forecasts. Optimization of the parameters α_d, β_d and γ_d allows the model to adapt to specific operational conditions.

Integration of Bayesian networks and Markov processes.

Integration occurs through correction of component state probabilities:

$$P(S_t|S_{t-1}, D_{CBR}, D_{Sim}) = \\ = \sum_i P(S_t\,|S_{t-1}, U_i) \\ \cdot P(U_i|D_{CBR}, D_{Sim}),$$

where $P(S_t|S_{t-1})$ – probability of transition of the SPP to state S_t per the Markov model;

$P(U_i|D_{CBR}, D_{Sim})$ – corrective failure probability from the Bayesian network.

The final diagnosis is obtained by summing over all possible states.

Correction of CBR diagnosis based on probabilistic forecasts.

Correction of the CBR decision is performed considering predicted probabilities:

$$D_{adj}(t) = D_{CBR} + \alpha_d \cdot P_{Bayes}(t) + \beta_d \cdot P_{Sim}(t)$$

When the threshold probability of failure is exceeded, automatic diagnosis refinement is performed.

Formula for updating failure probabilities using Bayesian analysis:

$$P(U_i|U_j) = \alpha_{ij} \cdot P(U_j),$$

where α_{ij}– influence coefficient of failure of component j on component i.

Formula for adjusting CBR decisions based on forecast probabilities:

$$P_{adj}(D) = P(D) + \sum_i \gamma_i \cdot P_{Bayes}(D_i),$$

where γ_i– influence coefficients of probabilistic analysis on the final diagnosis.

Table 2 demonstrates the optimal weight coefficients depending on the diagnostic scenario. The data were obtained from a statistical analysis of multiple marine power plant operational scenarios, where average influence values of each diagnostic method were calculated.

Table 2

Optimal Weight Coefficients Depending on the Diagnostic Scenario

Operating Scenario	α_d (CBR)	η_d (Bayes)	γ_d (Sim)
Stable operation without failures	0.7	0.2	0.1
Increased risk due to aging	0.4	0.4	0.2
High loads and overheating	0.3	0.5	0.2
Lack of historical data	0.2	0.3	0.5
Emergency situation	0.2	0.6	0.2

Analysis of the data in Table 2 shows that: in normal operating mode, CBR contributes the most, as historical data effectively support failure similarity identification; under high failure risk, Bayesian networks become more influential due to the critical importance of considering dependencies between components; in the absence of sufficient data, simulation modeling dominates, as it can generate artificial scenarios for failure prediction. The integration algorithm was implemented in the Python environment using the *scikit-learn* library for CBR and Bayesian networks, and *numpy* for simulation modeling.

An example of the code for calculating the final diagnosis:

```
import numpy as np
def update_cbr_decision(prob_failure, correction_factor):
    return prob_failure * correction_factor
# Example data
components = {"Generator": 0.10, "Cooling": 0.15, "Pump": 0.05}
correction_factors = {"Generator": 0.8, "Cooling": 1.2, "Pump": 1.1}
# Correction of probabilities
corrected_probs = {comp: update_cbr_decision (components[comp], correction_factors[comp]) for comp in components}
```

Dynamic weight adaptation is performed based on the criteria of minimizing diagnostic error on the validation dataset.

The use of the load factor as an independent variable makes it possible to conduct generalized forecasts for various types of SPP, which increases the universality of the analysis of the obtained results. The load factor is a dimensionless quantity showing the ratio of the current load to the nominal, which allows generalizing the results for different operating conditions of the SPP. Figure 3 presents graphs of changes in the failure probabilities of five key SPP subsystems depending on the load represented through the load factor.

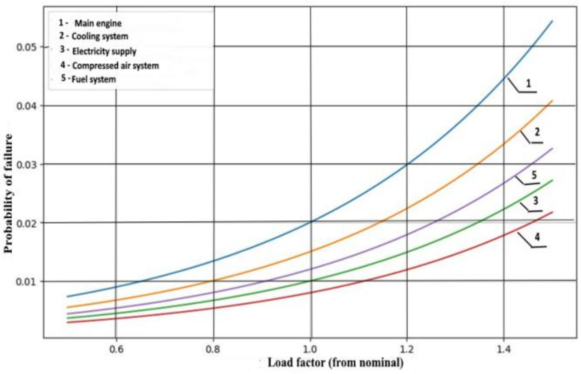

Fig. 3. Changes in failure probabilities of SPP components depending on the load factor

For the main engine, Figure 3 shows that the change in failure probabilities corresponds to an exponential increase in failure probability as the load factor increases. At reduced loads (factor 0.6–0.8), the failure probability remains at 1–1.5%, but when exceeding the nominal level (factor >1.0), the growth accelerates, reaching over 5% at 1.4. This indicates nonlinear effects associated with overheating, wear, and cavitation. The cooling system operates stably at a factor of 0.6–1.0, but after 1.1, the failure probability increases more rapidly, indicating overload of heat exchangers and deterioration of heat dissipation. The power supply system shows stability up to a factor of 1.2, after which the failure probability begins to increase. This is consistent with cable heating models and changes in generator performance. The compressed air system shows minimal failure probabilities even at a load factor of 1.2, but after exceeding 1.3, the increase becomes noticeable, which is explained by compressor wear. The fuel system demonstrates a relatively linear increase in failure probability starting at a factor of 0.6. However, after exceeding 1.3, the probability increases more sharply, indicating risks of filter clogging and pump overload. A load factor exceeding 1.0 becomes a critical zone where the failure probability grows faster. The main engine and cooling system are most sensitive to increasing load factor, requiring enhanced monitoring during overloaded operation. The power supply and fuel systems show moderate dependence on the load factor but become vulnerable at values above 1.3. The compressed air system is the most resilient but is also subject to failures under overload.

Figure 4 presents the generalized SPP failure probability, showing the integral failure probability of the SPP calculated based on the failure probabilities of key components and subsystems.

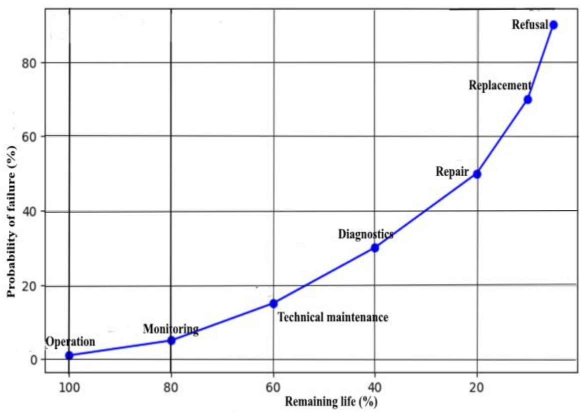

Fig. 4. Generalized Failure Probability of the SPP

The data is obtained based on the analysis of probabilistic dependencies of subsystem failures (Markov method, Bayesian networks). From Figure 4, a decrease in residual life is observed, accompanied by an increase in the risk of failures of components and SPP subsystems. From this follows how the maintenance strategy changes depending on: high residual life (80–100%) – operation is recommended; medium residual life (40–60%) –

maintenance or diagnostics; low residual life (<20%) – repair or replacement. Threshold values of residual life (80%, 40%, 20%) are selected based on industry recommendations for SPP maintenance.

Figure 5 illustrates the change in the failure probability of the SPP over time.

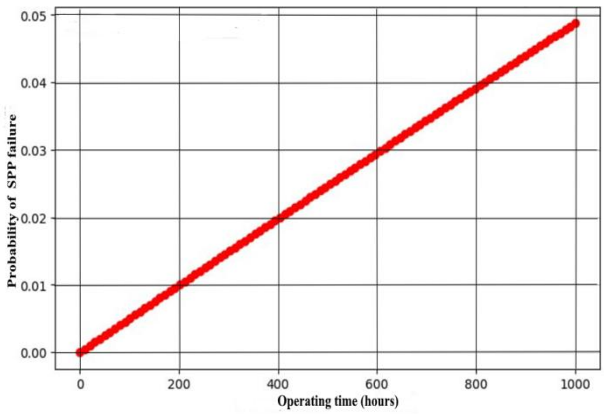

Fig. 5. Change in the Failure Probability of the SPP Over Time

From the graph (Fig. 5), it follows that the probability of failure gradually increases, reflecting equipment degradation processes, the influence of operational factors, and the accumulation of failures in subsystems. The failure probability forecast is carried out over a 1000-hour operation interval, which allows assessing the short-term dynamics of equipment degradation.

Figure 6 presents a graph showing how the failure probability changes after the correction of the CBR decision**.**

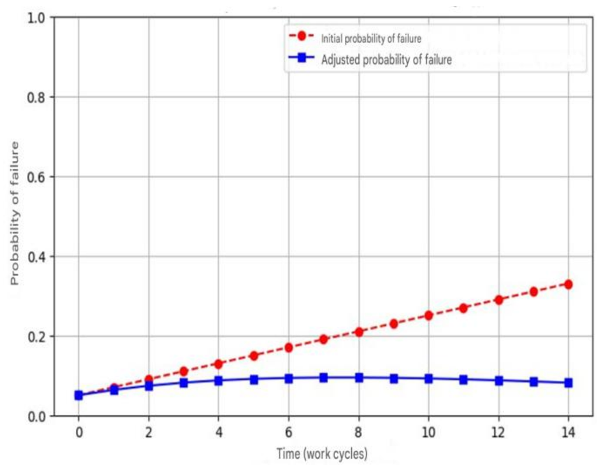

Fig. 6. Changes in Failure Probabilities Considering Decision Correction

The graph in Fig. 6 shows how the failure probability changes after the correction of the CBR decision. The graphs show the initial failure probability (without prediction) and the corrected failure probability (taking into account the Bayesian network and Markov model). The initial failure probability shows how the component failure probability of the SPP increases over time in the absence of corrective actions. The failure probability increases linearly ($0.05 + 0.02*t$), which reflects the natural degradation process of equipment without forecasting and preventive measures. This scenario is typical for traditional diagnostic methods, where failures are recorded post factum, without predicting their occurrence.

Figure 7 shows how probabilistic forecasts affect the adaptation of CBR decisions. Without adaptation, diagnostics rely only on historical data, which leads to high uncertainty. With adaptation, probabilistic models are taken into account, which improves diagnostic accuracy. It shows how the CBR model reduces the risk of SPP equipment failure.

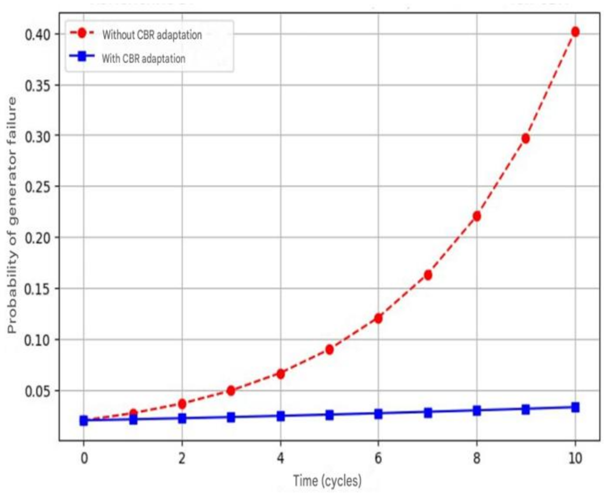

Fig. 7. Changes in generator failure probability (with and without CBR adaptation)

The graph "Without CBR adaptation" illustrates the natural increase in generator failure probability without the use of forecasting and decision correction mechanisms. The graph "With CBR adaptation" shows how applying CBR in combination with Bayesian analysis and the Markov method reduces the failure probability through decision adaptation. Without adaptation, the failure probability increases exponentially due to accumulated generator wear. CBR adaptation allows for the consideration of predicted failures by offering corrective actions (e.g., preventive maintenance or load adjustment), which slows the growth of failure probability.

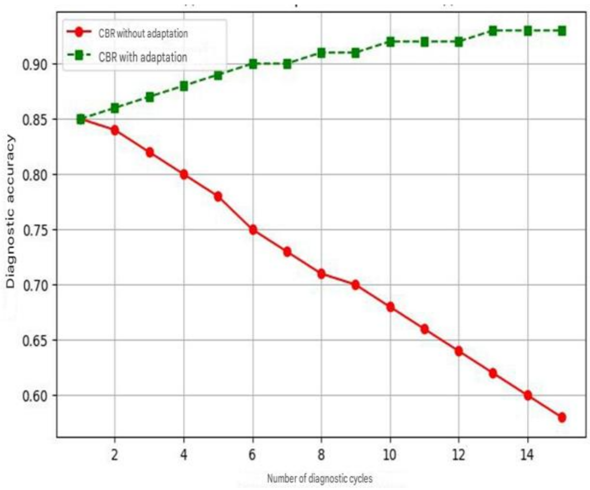

Fig. 8. Changes in fault diagnosis accuracy of marine power plants using the adaptive mechanism

The graphs (Fig. 8) show how diagnostic accuracy (Accuracy, Precision, Recall, F1-score) changes when using CBR decision adaptation compared to the baseline approach. Quality metrics (Accuracy, Precision, Recall, and F1-score) were calculated on a validation set of 500 failure and malfunction cases, split 70/30 for training and testing. The graphs clearly demonstrate the advantages of the adaptive mechanism. Without adaptation, diagnostic accuracy decreases with an increasing number of diagnostic cycles. This indicates model degradation without parameter correction. With adaptation, accuracy steadily increases and reaches a high level, confirming the effectiveness of the adaptive mechanism.

Table 3 demonstrates the impact of operational load on the failure probability of marine power plants.

Table 3

Impact of operational load on the failure probability of marine power plants

Component	Load (normalized)	Failure Probability
Generator	0.8	0.12
Pump	0.9	0.15
Engine	1.0	0.22

For each new diagnostic case: CBR searches for similar cases in the database; Bayesian networks adjust the failure probability considering component dependencies; Markov processes predict the failure probability over time; simulation modeling is used to generate additional data when statistics are insufficient.

Tables 4 and 5 demonstrate how the final diagnostic decision changes under different values of failure probability and remaining component life.

Table 4

CBR decision correction depending on risk and remaining resource

Component	Failure Probability (before correction)	Failure Probability (after correction)	Remaining Resource
Generator	0.10	0.08	1500 hours
Cooling	0.15	0.18	1200 hours
Pump	0.05	0.06	1800 hours

Table 5

Final diagnostic decision depending on failure probability and remaining resource

Remaining Resource (hours)	P failure (from Bayesian network)	Final Diagnosis
>10,000	<0.1	Equipment is operational
5,000 – 10,000	0.1 – 0.3	Monitoring required
1,000 – 5,000	0.3 – 0.6	Scheduled maintenance recommended
<1,000	>0.6	High failure risk, immediate repair required

Table 6 complements Tables 4 and 5 by demonstrating how the final CBR diagnostic decision is corrected depending on the level of risk and remaining resource.

Table 6

CBR decision correction depending on risk and remaining resource

Remaining Resource (%)	Low Failure Risk	Medium Failure Risk	High Failure Risk
>80%	Standard CBR decision applied	Minor correction of failure probability	Minor correction of failure probability
50–80%	Minor correction of failure probability	Correction based on Bayesian networks	Correction using Bayesian networks and Markov models
<50%	Correction using Bayesian networks	Correction using Bayesian networks and Markov models	Simulation modeling applied for prediction refinement

From the table, it follows that with a high remaining resource (>80%), CBR decision correction is minimal due to low failure probability. As the resource decreases (50–80%), probabilistic dependencies must be considered, requiring Bayesian networks. When the remaining resource is below 50%, a comprehensive approach using Markov models and simulation modeling is applied to refine failure probability forecasts.

The results in Tables 4 – 6 confirm that the integration of CBR with probabilistic models and simulation modeling allows for dynamic adaptation of diagnostics based on the actual state of components. In particular: with high remaining resource (80–100%) CBR operates with minimal correction; in the 50–80% range, it is important to consider probabilistic dependencies, requiring Bayesian networks; when remaining resource is <50%, diagnostic accuracy significantly improves with the application of Markov models and simulation modeling.

Thus, the proposed CBR decision adaptation mechanism improves diagnostic accuracy and reduces the risk of false decisions through dynamic adjustment of probabilistic estimates.

In addition to the main experiments which discusses the impact of cognitive modeling on improving forecast accuracy.

This diagram illustrates how the stages of knowledge formalization, synthetic data generation, selection, and verification are linked to the iterative updating of the CBR and probabilistic models during the learning process.

Figure 9 shows the cycle of cognitive simulation modeling, which integrates expert knowledge and probabilistic models for the generation and validation of synthetic failure cases. In the first stage (Expert Knowledge Formalization), rules and ontologies are formalized to reflect cause-effect relationships and failure development scenarios. Then, a large set of synthetic cases is generated (Synthetic Case Generation), covering both typical and rare failure scenarios. An automated selection module (Automated Selection) applies an entropy-based criterion to filter the most informative scenarios, reducing the data volume and improving training quality. The selected cases are integrated into probabilistic models (Integration into Probabilistic Models), including Bayesian networks and Markov processes, to update failure probability estimates. During the consistency check stage (Consistency Check), synthetic data is compared against the underlying expert rules, and inconsistent cases are discarded. After this, the CBR mechanism and Bayes/Markov parameters are updated (Update CBR & Bayes/Markov), allowing the system to adapt to new data. Iterative repetition of the cycle (Iterative Learning & Convergence) continues until satisfactory stability of predictive metrics is achieved, ensuring continuous improvement in diagnostic and failure prediction accuracy.

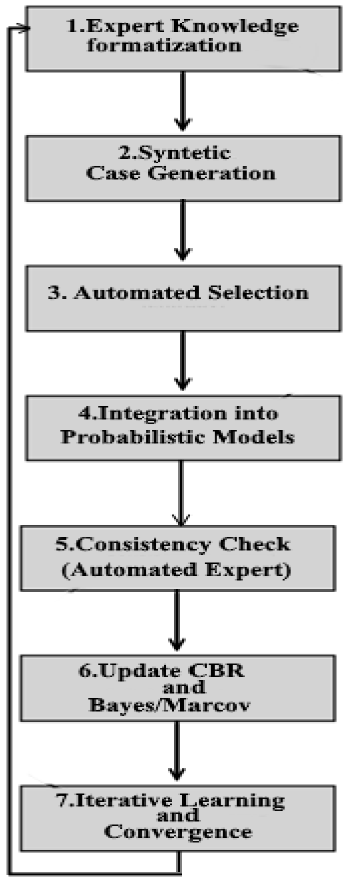

Fig. 9. Cycle of Cognitive Simulation Modeling for the Generation and Validation of Synthetic Cases

Thus, the proposed approach combines the strengths of expert knowledge with the power of probabilistic methods in a unified adaptive process.

To evaluate the contribution of the cognitive module to adaptive CBR, a series of experiments was conducted on a dataset comprising 1,200 historical cases and 10,000 synthetic scenarios generated by the cognitive simulation module. Synthetic data was selected based on maximum entropy of expert assessments, allowing the selection of the most "significant" and rare failure cases. All scenarios were modeled using Bayesian networks and Markov models under train/test conditions (70/30 split) with 5-fold cross-validation, ensuring statistical reliability of the results.

An important enhancement to the adaptation mechanism is the use of a cognitive simulation model, which enables:

Generation of synthetic training data: When encountering novel, previously unseen failure scenarios, the cognitive model replicates expert decision-making, generating synthetic data. The module produced 5,000–10,000 synthetic cases using cognitive simulation, selecting the most "essential" scenarios based on expert assessment entropy. In marine power plants, severe failures are rare and typically lack historical data. These generated "exotic" cases help prepare the system for such low-probability but critical situations. Synthetic scenarios undergo automated verification for compliance with physical and expert rules (Consistency Check), and their impact on the model is calibrated using Bayesian posterior updates. Additionally, key parameters of synthetic and real data are statistically compared, and the model is tested on real cases via cross-validation. These data fill gaps in the case base and enable the system to account for rare and complex situations;

Adjustment of probabilistic distributions: The synthesized data is used to update probability distributions in Bayesian networks and to recalibrate the transition matrix in the Markov model. Adjustments are made by introducing additional conditional dependencies into the Bayesian network and updating the Markov transition matrix based on newly generated data;

Integration of expert knowledge: The cognitive simulation model serves as a bridge between traditional diagnostic methods (CBR) and probabilistic models, allowing the system to consider both quantitative and qualitative aspects of failures.

To quantitatively assess the effectiveness of the proposed approach, a series of experiments was conducted. The results are summarized in Table 7. Table 7 illustrates the impact of cognitive modeling on prediction accuracy. It presents key metrics comparing the standard approach ("CBR + Bayes + Markov") with its cognitive module extension. Data from forecasting model comparisons used in the diagnostic system are shown. Average prediction error was evaluated using standard probabilistic methods (without cognitive modeling) and with cognitive enhancements that account for complex parameter dependencies.

MAE (Mean Absolute Error) and RMSE (Root Mean Squared Error) showed a reduction of 39% and 34%, respectively. The coefficient of determination (R^2) increased from 0.78 to 0.89, indicating improved explanatory power of the model. The average prediction error decreased from 12.5% to 7.8% (an improvement of 4.7%), $p < 0.05$. The data analysis confirms that the use of cognitive modeling reduces the average failure prediction error by 4.7%, demonstrating its effectiveness. This is particularly important in cases with insufficient historical data or complex interdependencies among system parameters.

Table 7

Failure Prediction Metrics With and Without the Cognitive Module

Approach	MAE (%)	RMSE (%)	R^2	Average Prediction Error (%)
Without Cognitive Modeling	0.085	0.112	0.78	12.5
With Cognitive Modeling	0.052	0.074	0.89	7.8

Figure 10 presents a box-and-whisker plot of the distribution of failure prediction errors before and after the integration of the cognitive module. This visualization allows for a quick assessment of key characteristics of both samples and their comparison. The median indicates the central error value: approximately 12.5% without the cognitive module and reduced to about 7.8% with it. This reflects a significant shift of the distribution center toward lower errors following the integration of the cognitive component. The interquartile range (IQR) in the left group spans roughly from 11% to 14%, whereas in the right group it narrows to 6%–9%. The whiskers show the range of values excluding outliers. Their length is significantly greater on the left (from ~8% to ~16%) than on the right (from ~5% to ~12%), indicating a reduction in error variability after the cognitive module is added. Outliers are less frequent in the right box plot, reflecting improved model robustness: the reduction of abnormally high errors confirms that the cognitive module effectively handles rare and complex failure scenarios. Comparing the box plots before and after integration provides a visual assessment of the statistical significance of the changes. Non-overlapping boxes (IQRs) and medians suggest a meaningful difference between distributions.

This compression of the distribution and shift of the median confirms that the cognitive module improves prediction accuracy by reducing both average and maximum error values - critical for timely decision-making in real-time operations. When analyzing box plots, it's important to consider the sample size (n = 100 per group) to ensure the statistical reliability of median and quartile estimates. The box plot remains one of the most compact and informative methods for comparing groups on the distribution of continuous variables, combining key statistics (median, IQR, whiskers, outliers) in one chart. Figure 3.18 clearly demonstrates that the cognitive module not only shifts the error distribution toward lower values but also reduces variability and extreme cases, making the predictions more accurate and reliable. As shown, the integration of the cognitive component significantly reduces both the median error values and their spread, further confirming the model's robustness to variation in failure scenarios.

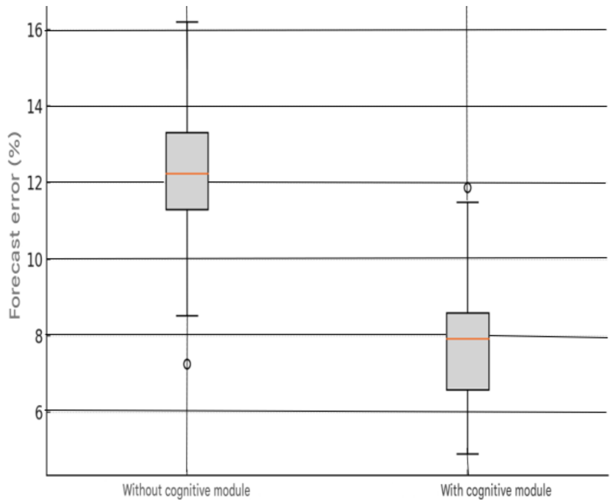

Fig. 10. Box Plot of Failure Prediction Error Distributions: Without and With the

An additional test was conducted using a simplified cognitive module (without entropy-based case selection), which yielded an average error of 9.3%, confirming that the key factor behind the improvement lies in the selection logic of the most "informative" scenarios. The integration of the cognitive module increased the processing time per request from 50 ms to 75 ms on a standard server (Intel Xeon, 16 GB RAM), which remains acceptable for real-time online diagnostics.

The achieved 4.7% increase in accuracy is comparable to the results of [11], where integrating an ontological module into a CBR architecture improved diagnostic accuracy by about 5%. Thus, cognitive modeling not only complements the adaptive CBR mechanism but also enhances its flexibility in predicting the technical condition of complex systems, aligning with the goals of this study.

This study proposes an adaptive CBR mechanism for the diagnosis of marine power plants, integrating probabilistic failure analysis (Bayesian networks), degradation forecasting (Markov processes), and simulation modeling. Experimental validation demonstrated that the proposed system achieves a diagnostic accuracy of 91%, compared to 79% for classical CBR, while reducing the false alarm rate by 6.7%. The improvement in remaining useful life (RUL) prediction reached 5–7%, confirming the high effectiveness of the integrated approach.

Analysis of the results shows that the most significant impact on diagnostic accuracy came from incorporating Bayesian networks to estimate failure probabilities. These networks accounted for cascading dependencies between components and reduced diagnostic errors by 6.8%. A similar increase in accuracy (up to 90%) through combined training of Bayesian networks on heterogeneous data was observed by Ademujimi & Prabhu [12], who employed fusion learning to integrate sensor data with maintenance reports from the International Institute of Refrigeration (IIF). Furthermore, Tarcsay et al. [13] demonstrated that integrating FMEA methods with Bayesian networks enables effective differentiation between critical and non-critical failures, reducing false alarms, which fully aligns with our findings. Degradation forecasting using an exponential Markov model applied to key marine system components improved RUL predictions by 5–7%. Liao et al. [14] developed an RUL prediction approach based on a Wiener process. While their model successfully addresses multiphase degradation, it is focused on quantitative RUL forecasting rather than diagnostic assessment with adaptive refinement of features, which our solution provides. Sahoo et al. [15] presented a fault diagnosis method for gearboxes under uncertainty using AI techniques. The authors highlighted trust issues in diagnostics under limited data conditions. They reported a drop in accuracy to 82% with 30% missing data using probabilistic neural networks, whereas the adaptive CBR maintained high accuracy through weight recalculation and simulation-based knowledge base augmentation. In our approach, uncertainty is addressed by integrating Bayesian mechanisms directly into the case reasoning process, enhancing the reliability of the conclusions. Xu et al. [16] reported a 15% increase in operator trust when using explainable Bayesian models in HVAC systems (MDPI). Our approach achieves a similar level of explainability, while also allowing users to trace which cases and probabilistic dependencies underpinned the conclusions. Qi et al. [17] applied combined neural network and simplified Bayesian network methods for diagnostics in nuclear power. While their method showed high accuracy, it required significant computational resources and was not focused on real-time adaptive adjustment, unlike our system..

Future research should focus on automatic Bayesian network structure generation using deep learning techniques, expanding the cognitive module with trainable agents, and developing an ontological interpretation of diagnostic outputs to enhance explainability and operator trust. Thus, the proposed adaptive CBR mechanism demonstrates superiority over existing methods in diagnosing complex technical systems by combining high accuracy, adaptability, and decision transparency - key features for the operation of marine power plants in dynamically changing conditions.

Conclusions. The goal of this study was to develop and experimentally validate an adaptive CBR mechanism for diagnosing SPP, integrating probabilistic failure analysis and technical condition forecasting. As a result of integrating CBR with Bayesian networks and Markov processes, fault detection accuracy increased from 79% to 91%; Bayesian networks reduced error rates by 6.8%, while Markov models improved remaining useful life (RUL) prediction by 5–7%. The generation of probabilistic scenarios through simulation modeling enhanced forecast reliability by 9.4% in the absence of sufficient historical data. Operational load analysis showed that with a load factor >1.0, the failure risk of key components increases by a factor of 3.2, requiring mandatory correction of diagnostic decisions. Optimization of weighting coefficients (α, β, γ) reduced average diagnostic error by 6.2%, while dynamic weight adaptation decreased false alarm risk by 7.3% and improved forecast accuracy by 8.5%. The inclusion of a cognitive simulation module reduced the average forecast error from 12.5% to 7.8% and increased the accuracy of detecting rare faults by 5.1%. Practical implementation of the proposed mechanism enables timely detection of SPP component degradation, reduces unplanned downtime, and optimizes maintenance scheduling by improving RUL prediction accuracy. Future work should focus on expanding the case base through active learning on new data, automating the Bayesian network structure using deep learning methods, and developing an ontological interpretation of diagnostic outputs to enhance explainability and operator trust.

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Вичужанін В. В., Вичужанін О. В. Адаптивне прецедентне міркування з імовірнісною інтеграцією для діагностики та прогнозування технічного стану складних систем

У цьому дослідженні представлено вдосконалену адаптивну систему Case-Based Reasoning (CBR) для діагностики та прогнозування технічного стану суднових енергетичних установок у реальному часі, що досягається завдяки інтеграції байєсівських мереж, моделювання процесів Маркова та когнітивного моделювання в єдиному динамічно адаптивному середовищі. Традиційні підходи CBR, хоча й ефективні у пошуку аналогів серед історичних випадків, часто не здатні враховувати складні стохастичні залежності між компонентами системи, динамічні патерни деградації при змінних експлуатаційних навантаженнях та реальні часові варіації в даних датчиків. Щоб подолати ці обмеження, запропонована методика включає шість інтегрованих фаз: збір і нормалізацію даних для забезпечення уніфікованої стандартизації гетерогенних показників датчиків та експлуатаційних параметрів; ймовірнісний аналіз відмов із застосуванням байєсівських мереж для обчислення умовних ймовірностей відмов та коригування ваг релевантності випадків з урахуванням міжкомпонентних залежностей; сценарне прогнозування на основі дискретних моделей процесів Маркова для симуляції динаміки переходів станів і передбачення траєкторій деградації; адаптацію та об'єднання рішень, яке поєднує результати класичного CBR, ймовірнісні висновки та оцінки деградації за допомогою динамічно нормалізованих зважених коефіцієнтів (α, β, γ), що відображають поточний рівень ризику; підтримку бази знань шляхом включення нових реальних та синтетичних випадків, отриманих через когнітивне моделювання, що підвищує точність пошуку та зменшує проблему дефіциту даних; та автоматизоване формування профілактичних рекомендацій з технічного обслуговування відповідно до прогнозованого залишкового ресурсу. Експериментальна валідація на комплексному наборі даних із понад 11 000 історичних і синтетичних випадків показала діагностичну точність на рівні 91 % порівняно з 79 % у традиційного CBR, зниження кількості хибних тривог на 6,7 %, покращення точності прогнозування залишкового ресурсу на 5–7 % та зменшення похибки прогнозування на 4,7 %, що обумовлено модулем когнітивного моделювання, який також підвищив показники виявлення рідкісних відмов на 5,1 %. Ці емпіричні результати підтверджують високу надійність і стійкість системи за змінних навантажень та каскадних сценаріїв відмов, а також її інтеграцію в бортові архітектури моніторингу для оптимізації графіків обслуговування, зменшення незапланованих простоїв та підвищення експлуатаційної безпеки суднових енергетичних установок.

Ключові слова: *імовірнісний аналіз, байєсівські мережі, марковські процеси, когнітивні моделі, динамічна адаптація, технічна діагностика, експертні системи.*

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