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DYNAMICS OF FAILURE PROBABILITIES IN SHIP POWER PLANT EQUIPMENT CONSIDERING CASCADE EFFECTS

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ДИНАМІКА ЙМОВІРНОСТЕЙ ВІДМОВ В ОБЛАДНАННІ СУДНОВОЇ ЕНЕРГЕТИЧНОЇ УСТАНОВКИ З УРАХУВАННЯМ КАСКАДНИХ ЕФЕКТІВ

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The article presents a comprehensive and scientifically substantiated approach to modeling the technical condition, degradation processes, and reliability of ship power plants (SPP) considering cascade failure effects and probabilistic dependencies between components. A hybrid diagnostic–prognostic methodology is proposed, integrating continuous-time Markov processes, Bayesian networks, gradient boosting algorithms (XGBoost), and simulation modeling within a unified analytical framework. The approach enables quantitative assessment of the dynamic evolution of reliability under complex interactions between subsystems. The interrelation between SPP components is formalized through a cascade influence coefficient matrix α_{ij}, which reflects how the malfunction of one unit increases the probability of failure in another. Bayesian networks are used to capture causal relationships between failures and to continuously update probabilistic assessments based on new monitoring data, while machine learning algorithms determine the most informative parameters for predictive diagnostics, such as vibration amplitude, oil temperature, and cooling system pressure. The model was trained and validated using operational data from the OREDA database and expert evaluations, demonstrating high predictive accuracy ($AUC > 0.95$, $MAE < 4.7\%$). Simulation experiments identified two critical operational intervals (≈10,000 and 20,000 hours), when cascading effects lead to exponential growth of total failure probability. The cooling system and main engine were found to be the most vulnerable nodes initiating degradation chains that propagate throughout the system. The developed methodology enables integration into digital twin architectures for adaptive recalibration, anomaly detection, and risk-based maintenance optimization. The study contributes to the formation of a data-driven, cognitive basis for intelligent monitoring and predictive maintenance of maritime energy systems, enhancing their reliability, resilience, and operational efficiency under uncertainty and extended service life.

Keywords: *probabilistic modeling; cause-and-effect relationships; technical condition diagnostics; Bayesian networks; simulation modeling; machine learning in maintenance; equipment reliability*

Introduction. Ship power plants are critically important elements of maritime infrastructure, with their reliability directly determining the uninterrupted operation of a vessel under conditions of prolonged loads and variable external factors [1, 2]. Their design represents a complex combination of interconnected components functioning as a unified whole. In such conditions, failures of individual units may lead to cascade processes that can significantly accelerate the degradation of the system as a whole. Considering these cascade effects in diagnostic and prognostic models remains one of the least developed but potentially critical tasks in technical diagnostics. Modern research demonstrates progress in the field of reliability assessment for complex technical systems (CTS), yet most studies are either limited to individual equipment or do not consider their systemic interdependencies. Moon et al. [3] applied a multistage Markov model to analyze the degradation of marine components. While the model successfully reflects the reliability dynamics of individual CTS elements, it does not account for probabilistic dependencies between components, which significantly limits its applicability in the case of cascading equipment failures. The Markov maintenance model developed by Garbatov and

Georgiev [4] takes into account degradation and carbon efficiency indicators. The work is relevant in the context of maintenance planning, but the authors focus on individual degradation trajectories without analyzing interactions between units, reducing the applicability of the approach for integrated risk assessments. The probabilistic methodology by Morato et al. [5] for analyzing equipment failures in CTS considers mutual dependencies between components. Bayesian networks combined with reinforcement learning were used for dynamic decision-making. Cascade effects in this work are considered through structural probabilistic links: if one component fails, the probability of another failing increases. This brings the model closer to the reality of complex systems. However, Morato et al.'s model focuses on a general reliability management framework and does not include temporal failure dynamics, i.e., it does not describe how quickly the cascade spreads after initiation. Moreover, there is no formalized quantitative relationship between components (e.g., influence coefficients of failures), which limits its application in tasks where the degradation sequence detail is critical. The problem of decision-making under uncertainty based on partially observable Markov processes was studied by Andriotis et al. [6]. The model allows for the possibility that system components are interconnected, and information on their condition has different values. Thus, interdependencies between components are possible and partially considered, including in monitoring strategy selection. However, the work lacks an explicit formalization of cascade effects: it does not show how one component's failure affects the failure probability of others, nor are structural or quantitative parameters of such links introduced. Furthermore, the study focuses on abstract engineering systems and is not adapted to the specifics of marine MPPs, which hinders practical application in marine diagnostics. Kamariotis et al. [7] proposed a framework for assessing the value of vibration-based monitoring, which can be used for early degradation detection. Despite its importance, this work does not consider interactions between components and is limited to evaluating a single data type (vibrations) without using comprehensive probabilistic models. The most relevant studies for diagnostics are those based on machine learning. Raptodimos and Lazakis [8] applied NARX neural networks to predict marine engine parameters, and Cheliotis et al. [9] implemented a failure detection system based on neural models. Both studies confirm the high sensitivity of models to operational parameters; however, they do not address cause-and-effect relationships between component failures and do not formalize state transitions. Zhu et al. [10] studied multiple failures of marine diesel engines using various neural network architectures, including CNN and RNN. Their model demonstrates high diagnostic accuracy, but the focus is on state classification rather than modeling the probabilistic failure dynamics within a system structure. Of particular interest is the study by Wang et al. [11], which proposed an intelligent diagnostic scheme based on principal component analysis and backpropagation in a neural network. The approach effectively detects anomalies but does not account for temporal dynamics or mutual influences among components.

Thus, despite significant advances in technical condition forecasting, key methodological problems remain unresolved: lack of formalized consideration of cascade interactions between SPP components; insufficient integration of temporal degradation models (e.g., Markov processes) with cause-and-effect relationships (Bayesian networks); limited use of machine learning as a tool for probabilistic inference support; weak linkage between diagnostic results and preventive maintenance strategies; absence of models for rare multiple failures during prolonged operation. The purpose of this study is to investigate the dynamics of component failure probabilities in SPPs considering cascade effects and to develop an integrated prognostic methodology combining probabilistic modeling, machine learning, and simulation.

To achieve this goal, the following tasks are addressed:

1. Construct a mathematical model of cascade effects between SPP components using an influence matrix α_{ij}.
2. Simulate the temporal degradation of components using continuous Markov processes.
3. Apply Bayesian networks to refine failures based on cause-and-effect relationships.
4. Use machine learning algorithms (XGBoost) to analyze operational data and assess risk factors.
5. Perform correlation analysis of failure data (OREDA, 25,000 hours) to identify interdependencies.
6. Visualize the propagation of cascade effects using heat maps and network graphs.
7. Conduct simulation modeling of rare multiple failure scenarios.
8. Formulate recommendations for optimizing maintenance based on time-based risk thresholds (10,000 and 20,000 hours).

Results

Formalization of cascading effects.

To describe the cascading propagation of failures among interconnected SPP equipment, an approximate model is introduced for the change in failure probability *$P_i(t)$*, analogous to a difference equation accounting for the influence of other system components:

$$P_i(t+\Delta t) = P_i(t) + \sum\nolimits_{j\neq i} a_{ij} \cdot P_j(t) \cdot \Delta t,$$

where $P_i(t)$ is the probability of failure of component i at time t;

$P_j(t)$ is the probability of failure of component j at time t;

a_{ij} is the influence coefficient of component j on the failure probability of component i;

Δt is the time step

This model reflects the impact of simultaneous wear and degradation of interconnected components and makes it possible to account for cascading failure propagation within the system. The values of the coefficients a_{ij} are determined based on correlation analysis and simulation modeling and represent empirically derived dependencies.

Based on the data on mutual influence of failures among key SPP components, a matrix of influence coefficients $A=[a_{ij}]$ was constructed. The rows of the matrix correspond to the influenced component i, and the columns to the influencing component j. The coefficients a_{ij} , representing the impact of the failure of component j on the failure probability of component i, were obtained from: correlation analysis of historical failure data for MPPs over 25,000 hours of operation; expert evaluation, harmonized with simulation modeling results (including those based on the OREDA [12] database); analysis of rare failure scenarios using cognitive models and Bayesian networks, which define conditional probabilities. These values are not universal but adequately reflect the behavior of typical SPP s during long-term operation and can be adapted to a specific facility if failure statistics are available. The proposed formalization of cascading effects has several methodological limitations. The model is described by an approximate difference equation reflecting a linear dependency between components. This structure ensures implementation simplicity, calculation transparency, and adaptability, but it does not take into account, for example: time delays in the propagation of failures; nonlinear amplifications under multiple influences; potential synergistic effects. Furthermore, the current version does not utilize structural characteristics of the cascading dependency graph, such as depth, density, cycles, or the presence of redundant propagation paths. These aspects may be critical when analyzing complex technical systems. Future development directions for the model include: incorporating temporal influence weights; transitioning to continuous representations; integration with dynamic logic-probabilistic models. Such extensions would improve the description of cascading processes and enhance the accuracy of predictions in systems with high component interdependence.

The cascading dependency graph, constructed based on the matrix α_{ij}, represents a directed weighted network, in which nodes correspond to SPP components, and arcs reflect the directed influence of failures. The weight of an arc determines the strength of the effect one component has on another. This type of graph allows for visualization of failure propagation routes and identification of the most vulnerable or critical nodes. An example of such a structure is shown in Figure 1.

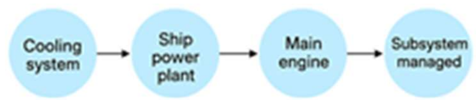

Fig. 1. Network graph of cascade effects

Despite the apparent simplicity of the basic difference equation, the structure of the proposed model allows for further theoretical expansion. Below is a possible formalism that describes cascade dynamics in a more comprehensive form. It can be implemented as part of an advanced prognostic platform, given the availability of detailed data and computational resources. Taking into account the outlined limitations, a generalized mathematical framework is proposed for describing cascading failures in complex technical systems. It integrates probabilistic dynamics, structural dependencies, and adaptive forecast correction. The formalization includes the following components:

<u>Temporal dynamics of component degradation</u>**.** Each system element i is associated with a Markov process [13] with a set of technical states of the SPP equipment {0, 1, 2, 3}, representing stages of technical life (operational, degraded, pre-failure, failure). Transitions between states are defined by the matrix $Q^{(i}$, and the evolution of the probability vector is given by the equation:

$$\frac{dP_i(t)}{dt} = P_i(t) \cdot Q^{(i)}$$

where: $P_i(t) = \left[P_i^{(0)}(t), P_i^{(1)}, (t)P_i^{(2)}, (t)P_i^{(3)}(t)\right]$ - the probability vector of component *i* being in one of four states at time *t*;

$Q^{(i)} =\in R^{4x4}$ - the transition rate matrix (infinitesimal generator) of the Markov process for component *i*;

$P_i^{(k)}(t)$ - в the probability that component *i* is in state $k \in \{0,1,2,3\}$ at time *t*

Graph of cascade interdependencies. The structure of cascading influences is represented by a directed weighted fault graph:

$$G=(V,E),$$

where: $V = \{v_1, v_2, \dots, v_n\}\}$ - the set of vertices, each corresponding to a component of the SPP;

$E =\subseteq V \times V$ - the set of directed edges, each edge (j → i) reflects the potential influence of the failure of component *j* on component *i*,

$V \times V = \{(v_i, v_j) | v_i \in V, v_j \in V\}$;

$\alpha_{ij} \in [0,1]$ - the weight of the edge, reflecting the strength of such influence (empirically determined).

The weight α_{ij} reflects the strength of the influence [14]. The cascading contribution of component *j* to the failure probability of component *i* is defined by the expression:

$$\widetilde{P_i}(t + \Delta t) = P_i(t + \Delta T) + \sum_{j \in N(i)} a_{ij} \cdot (P_j^{(2)}(t) + P_j^{(3)}(t)) \cdot \Delta t$$

where: $\widetilde{P_i}(t + \Delta t)$ - the adjusted failure probability of component *i*, taking into account the cascading influence of neighboring components;

$P_i(t + \Delta T)$ - the baseline failure probability of component *i*, calculated without considering cascade influence (e.g., from the Markov model);

$N(i) \subset V$- the set of components that exert influence on component *i*, i.e., its cascade predecessors;

$P_j^{(2)}(t)$ - the probability that component *j* is in a pre-failure state (state 2) at time *t*;

$P_j^{(3)}(t)$ - the probability that component *j* is in a failed state (state 3) at time *t*

Causal dependencies. The use of Bayesian networks allows for accounting of conditional dependencies between failures and updating probability estimates during operation [15]. To describe causal relationships between component failures, the basic Bayes' formula is used:

$$P(A|B) = \frac{P(B|A) \cdot P(A)}{P(B)}.$$

where: *A* and *B* are failure events of components;

$P(A|B)$- the probability of failure of component *A* given failure of component *B*;

$P(B|A)$ - the probability of the reverse dependency

Continuous approach. In the continuous formulation, the failure probability of component *i* is described by the integral equation of accumulated SPP equipment failure risk [16]:

$$P_i^{(3)}(t) = P_i^{(3)}(0) + \int_0^t \left[\lambda_i(t) + \sum_{j \neq i} a_{ij} \cdot P_j^{(3)}(t)\right] dt$$

where: $\lambda_i(t)$ - the intensity of intrinsic degradation processes in the SPP

Integrated model structure. The developed architecture integrates temporal, topological, and causal-probabilistic dynamics. It adapts to operational data using machine learning methods such as gradient boosting, which refine the importance of features (vibration, temperature, pressure) and the structure of the Bayesian network. Thus, the formalization of cascade effects in the proposed model relies on both analytical expressions and a graph-based representation of inter-component connections, allowing for quantitative prediction of failure propagation and identification of components that initiate cascade processes.

Integrated methodology for cascade failure analysis of SPP equipment. The proposed methodology implements a hybrid architecture for prognostic analysis, combining three levels: temporal (Markov processes), structural (Bayesian networks), and empirical (XGBoost). This architecture reflects both the physical degradation of components over time and probabilistic inter-component dependencies supported by operational data. It includes the following key stages:

1. Formalization of the SPP structure. The hierarchy and composition of functional units are defined, including the main engine, ship power plant, cooling system, control subsystem, and other equipment. The structure is represented as a directed graph where nodes correspond to components, and

edges indicate possible paths for failure propagation.

2. Modeling of temporal degradation. For each component, a degradation model based on continuous-time Markov processes is introduced, with transitions between the following states: operational, degraded, pre-failure, and failure. Transition probabilities are calibrated using long-term operational data (25,000 hours). Each component is modeled with four technical states: 0 - operational condition (no signs of failure); 1 - degradation (minor parameter deviations, still functional); 2 - pre-failure state (critical decline in functionality); 3 - total failure (component is non-functional).

Transitions between these states are described using a transition probability matrix Q, derived from statistical data over 25,000 hours of operation. Transition probabilities are updated according to the equation:

$$P(t + \Delta t) = P(t) \cdot Q,$$

where: $P(t)$ – the state probability vector at time t

1. Determination of cascade influence coefficients. To account for inter-component effects, an influence coefficient matrix α_{ij} is constructed. It reflects the probability that the failure of component j will increase the risk of failure of component i. These coefficients are obtained through correlation analysis, simulation modeling, and expert calibration (including the use of the OREDA database). For example, the failure of the cooling system may increase the probability of main engine failure by 25%. The matrix α_{ij} is also used in constructing the directed graph (Fig. 1), where arrows represent directed cascade dependencies.

2. Bayesian correction. To refine failure probabilities in real time, a Bayesian network model is used. The network formalizes conditional dependencies between components using the expression:

$$P(A|B) = \frac{P(B|A) \cdot P(A)}{P(B)},$$

where A and B are specific technical components (e.g., main engine and power subsystem), and the corresponding probabilities are updated based on monitoring data.

This enables dynamic adaptation of the model to current operational conditions. When new data becomes available (e.g., increasing vibration or temperature), probabilities are recalculated using Bayes' rule, adapting the forecast to current conditions. The Bayesian network accounts for reverse dependencies and helps identify initiating and relaying components in the failure cascade. A visualization of the probabilistic dependency structure is shown in Fig. 2.

3. Feature importance evaluation. To assess the impact of parameters on fault tolerance, the XGBoost gradient boosting algorithm was applied. The model was trained on operational data spanning 25,000 hours (OREDA), and identified key risk indicators: oil temperature, vibration, and cooling system pressure. For example, the probability of generator failure increases by 15% when vibration exceeds the normal level by 20%; the impact of cooling system wear on main engine failure reaches 22%. The analysis results are used both to define the structure of the Bayesian network and to pre-filter scenarios in the simulation model.

4. Simulation modeling. The developed model is integrated into a simulation framework, where rare but potentially critical multi-failure scenarios are simulated using random event generation. This enables evaluation of the SPP configuration's resilience to cascading failures.

5. Temporal threshold analysis. Based on the simulations, characteristic operational intervals were identified during which the probability of cascading failure increases exponentially (e.g., at 10,000 and 20,000 hours). This allows for establishing benchmarks for preventive maintenance scheduling.

The proposed methodology provides a comprehensive assessment of SPP reliability, allowing consideration of both individual degradation processes and their mutual amplification through cascades. Its advantage lies in the ability to adapt to a specific asset based on actual failure statistics.

To demonstrate the functioning of the proposed approach, a scenario is provided in which the integration of methods enables tracking and forecasting of cascading failure development, starting with the deviation of a single parameter. Each step of the algorithm is aimed at timely detection and containment of the degradation chain: the system detects an increase in vibration above the allowable threshold (by 20%); the Bayesian network updates the posterior failure probabilities of related components (e.g., generator and main engine); the Markov model predicts the generator's transition into a pre-failure state within 5,000 hours; the simulation model initiates a cascading failure scenario, showing the probability of critical node involvement; the system generates a decision to enhance monitoring, adjust maintenance schedules, and implement preventive actions to break the cascade chain.

Analysis of failure dynamics of SPP equipment. Based on the performed calculations, graphs showing the time-dependent probability of equipment failures in the SPP were constructed (Fig. 2).

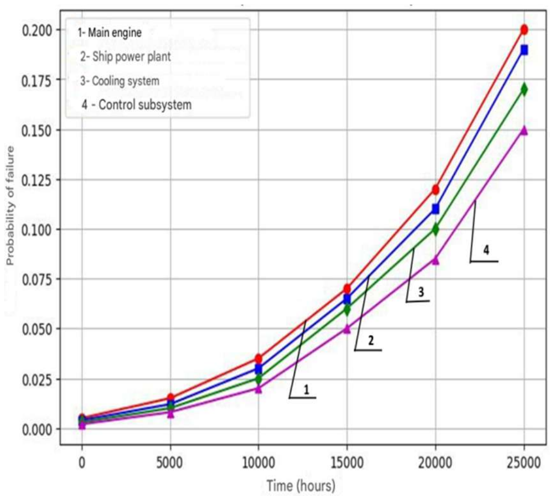

Fig. 2. Charts of failure probability variation of SPP equipment over time

The charts (Figure 2) and Table 1 show the dynamics of failure probabilities for various SPP equipment depending on operating time (up to 25,000 hours). The main engine has the highest failure probability among all components. By 25,000 hours of operation, the failure probability reaches approximately 20%. The main risk factor is the high load and wear of the engine's main components. The marine power plant has a slightly lower failure probability than the main engine but follows a similar trend. By 25,000 hours of operation, the failure probability is approximately 19%. Key risks are associated with overloads and equipment aging: the cooling system has a lower failure probability than the main engine and the power plant but increases significantly toward the end of the studied operating period. By 25,000 hours, the failure probability is approximately 18%. Possible causes: fouling of heat exchangers, leaks, and corrosion; the control subsystem is the least prone to failure compared to other components. By 25,000 hours, the failure probability is approximately 16%. Main threats: software failures, sensor degradation. Thus, the main engine is the most vulnerable component requiring enhanced monitoring and predictive maintenance; the marine power plant and cooling system are also subject to significant failure risks, especially with extended service life; the control subsystem has the lowest failure probability but plays a critical role in the reliability of the entire system, so its failures may lead to cascading effects. The general trend is an exponential increase in failure probability after 15,000–20,000 hours of operation, which confirms the need for predictive maintenance. Recommendations: implementation of monitoring and diagnostic systems for the main engine and power plant; use of predictive maintenance using machine learning methods; enhanced control over the cooling system to prevent overheating and leaks; continuous updating of the control subsystem software to minimize failures due to algorithm errors.

Table 1

Dynamics of failure probabilities of key SPP /equipment over time

Time (hours)	Main engine	SPP	Cooling system	Control subsystem
0.005	0.004	0.003	0.002	0.005
5000	0.015	0.012	0.010	0.008
10000	0.035	0.030	0.025	0.020
15000	0.070	0.065	0.060	0.050
20000	0.120	0.110	0.100	0.085
25000	0.200	0.190	0.170	0.150

Analysis of Table 1 data reveals three key time intervals based on the rate of failure growth. During the first 5,000 hours of operation, there is a relatively slow increase in failure probabilities, reflecting the normal functioning mode of the equipment. Between 10,000 and 15,000 hours, an accelerated growth in risk begins, indicating the manifestation of accumulated wear and strengthening of inter-component interactions. After 20,000 hours, failure resilience decreases significantly, especially for mechanically loaded units, which necessitates a transition to active maintenance measures. The overall trend highlights the need to implement predictive approaches to prevent a sharp increase in failure rates.

Analysis of influence coefficients in matrix $A = [a_{ij}]$ (Table 2) shows the following strong interdependencies: cooling system and marine power plant: failure of one component increases the failure probability of the other by 30%; main engine and control subsystem: malfunction in the control system increases the engine’s failure probability by 25%.

Table 2

Cross-influence coefficients of SPP equipment failures

Component *i*	**Component *j***	α_{ij}
Main engine	SPP	0.20
Main engine	Control subsystem	0.25
SPP	Cooling system	0.30
Control subsystem	Main engine	0.20

According to Table 2, cascade effects significantly accelerate the failure process after 10,000 hours of operation, the probability of failures increases non-linearly. The most vulnerable to cascading failures are the cooling and control systems, as their malfunctions substantially increase the likelihood of failures in other components. The results of this analysis can be used to develop preventive maintenance strategies aimed at reducing the probability of critical failures through proactive measures at key operational nodes. This analysis confirms the importance of an integrated approach to SPP failure diagnostics, taking into account the interdependent failure probabilities of various components.

The impact of a single component's failure on the failure probabilities of other components, as well as on the risk of total loss of operability (TLO), is presented in Table 3.

Table 3

Cascade dependency matrix between SPP components

Failed Component	**ME**	**SPP**	**CS**	**CSUB**	**FS**	**GEN**	**TLO**
Main Engine (ME)	1.00	0.25	0.30	0.20	0.15	0.10	0.85
SPP	0.20	1.00	0.25	0.15	0.10	0.30	0.80
Cooling System (CS)	0.30	0.20	1.00	0.25	0.15	0.10	0.78
Control Subsystem (CSUB)	0.25	0.20	0.30	1.00	0.10	0.15	0.75
Fuel System (FS)	0.15	0.10	0.10	0.05	1.00	0.20	0.60
Generator (GEN)	0.10	0.30	0.10	0.15	0.20	1.00	0.70

The analysis of the cascade dependency matrix between components of the marine power plant (Table 3) reveals structural features of cascade effect propagation within the system. The influence of one component on another is expressed not only through local coefficients but also via the cumulative metric of TLO, which reflects each element's integral contribution to the overall resilience of the system. The highest TLO value (0.85) is recorded for the failure of the main engine, indicating its central role in initiating and amplifying cascading processes. A main engine failure significantly increases the likelihood of failure in several critical components: the cooling system (+30%), the power plant (+25%), and the control subsystem (+20%). This confirms its status as the primary risk generator in the system. A high TLO is also observed for the marine power plant (0.80), which acts as a retransmitter of failures, especially influencing the generator (+30%) and the cooling system (+25%). The cooling system demonstrates a similar pattern of impact, causing increased failure probabilities in the control subsystem (+25%) and the main engine (+30%), which is due to its functional connection with thermal and hydraulic circuits. The control subsystem, despite a lower TLO (0.75), exerts critical influence on the mechanical part of the plant: its failure raises the likelihood of engine failure by 25% and that of the cooling system by 30%. This reflects the logical dependency of system control on physical processes, as well as the inverse vulnerability of control systems to mechanical faults. Components with the lowest TLO fuel system (0.60) and generator (0.70) exhibit relatively weak influence on other elements. However, even in these cases, dependencies are identified that suggest the possibility of secondary cascade effects. For example, generator failure increases the risk of power plant failure by 30% and of the fuel system by 20%. The overall structure of mutual influences in Table 3 is not symmetrical, highlighting the directionality of cascade effects. The impact of components varies in both magnitude and direction: the same element may act as a serious failure initiator while being only marginally affected by the failure of others. This is characteristic, for example, of the main engine, which has a strong influence on the system but experiences moderate reciprocal impact from most units. Thus, the table of influence coefficients not only formalizes local risks but also provides insight into the system's global resilience. Components that act as both triggers and retransmitters of failures have been identified. These data serve as a foundation for prioritizing components for monitoring and preventive maintenance. In particular, the main engine, power plant, and cooling system require special attention, as their failure significantly increases the overall risk of cascading failures throughout the plant.

Based on the data presented in Table 3, it is necessary to adjust the maintenance strategy for the SPP. The main engine and the power plant should be serviced most frequently, as their failures lead to the most severe consequences.

Development of backup systems. The generator must be equipped with emergency backup circuits to prevent cascading failures in the electrical system.

Failure prediction. The data from the table can be integrated into a CBR + Bayesian analysis algorithm [17, 18], where the impact level of a component's failure is used to recalculate probabilities during the diagnostic process. To identify interdependencies between failures of various SPP components, a failure risk heat map has been constructed (Figure 3). This map visualizes the probabilities of failure propagation from one component to another.

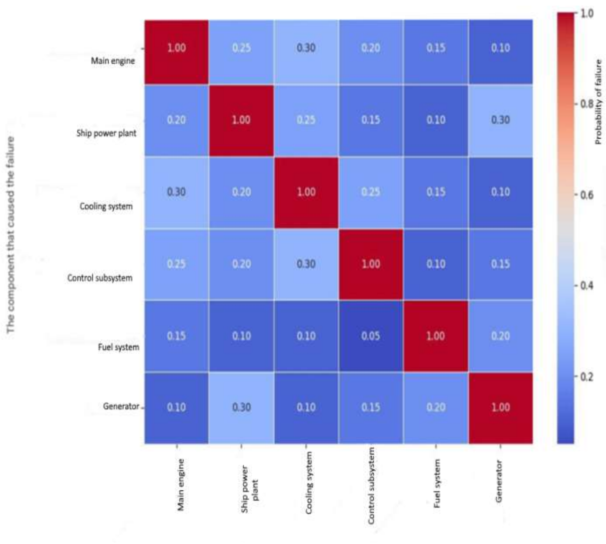

Fig. 3. Heatmap based on interdependencies of SPP component failure risks

The heatmap shown in Figure 3.36 provides a visual assessment of the intensity of cascading interactions between components of the SPP. The dependencies displayed are a graphical interpretation of the numerical values from the cascade influence matrix (Table 3), where each pair of components reflects the degree to which the failure probability increases when a related node fails. The most saturated zones of the diagram correspond to system elements that either exert the strongest cascading impact on other nodes or are most affected by others. This structure confirms the results obtained from the quantitative analysis and emphasizes the importance of prioritizing monitoring and maintenance efforts for nodes with the highest cascading potential. The visualized data can be integrated into the implementation of the hybrid prognostic analysis architecture presented at the beginning of the section. This architecture includes: a temporal level (based on Markov processes) reflecting the degradation dynamics of components; a structural level (Bayesian networks) formalizing the cause-and-effect relationships between failures; an empirical level, using machine learning algorithms (e.g., XGBoost) to identify risk factors based on operational data. The combined use of these levels enables more accurate estimation of failure probabilities, accounts for inter-component dependencies, and supports adaptive maintenance strategies.

Figure 4 presents a network graph that illustrates the sequence of cascading failures in the SPP, the interconnections between key components, and the probability of their failure under the influence of preceding events. The structure of inter-component influences is represented as a directed graph, where the arc weights correspond to the coefficients α_{ij}.

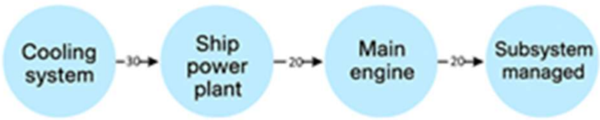

Fig. 4. Network graph of cascading effects

The network graph illustrates the propagation of failures within SPP. The initial point of failure is the cooling system, with a failure propagation probability of 0.30 to the ship's power station. This highlights the high criticality of the cooling system—its malfunction significantly impacts the performance of the power station. The ship power station is susceptible to cascading failure originating from the cooling system. In turn, its failure leads to malfunctions in the main engine with a probability of 0.20. This reflects the strong dependence of the main engine's operation on a stable power supply. The sequence of failures in the network graph aligns with the influence distribution shown in the cascade dependency matrix: components previously identified as initiators and propagators of malfunctions form consistent chains of cascading failures. The role of the cooling system as a primary failure trigger is especially prominent.

In summary, the key vulnerable component is the cooling system. Its failure initiates a cascade affecting the entire system. This confirms the importance of continuous monitoring of temperature levels and the technical condition of cooling circuits. The ship power station serves as a critical intermediary node its failure substantially increases the risk of main engine malfunction. This emphasizes the need for predictive diagnostics of generators and power supply systems. The control subsystem shows relative resilience; while failures are possible, they are more likely consequences of mechanical system malfunctions than primary causes.

Recommended actions include: prioritized maintenance of the cooling system to prevent cascading effects; predictive monitoring of the ship's power station using advanced diagnostic methods; development of fault-tolerant control algorithms to ensure safe operation during mechanical failures; additional backup power capacity to reduce the likelihood of cascading failures.

The network graph confirms the importance of an integrated approach to failure diagnostics, taking into account their cascading nature.

Correlation analysis: identifying hidden dependencies. A correlation analysis was conducted based on component failure data. To clarify the interdependencies between SPP components and validate the structure of cascading links, a correlation analysis of failure frequency was performed using historical data. The results are presented in the form of a correlation matrix, which reveals statistically significant relationships between failures of key units. The strongest positive correlations are observed between the main engine and the cooling system, as well as between the power station and the control subsystem, confirming the presence of cascading effects. The resulting correlation coefficients were used as an additional basis for constructing the Bayesian network structure and calibrating the influence coefficients α_{ij}. A visual representation of these dependencies is shown in Figure 5.

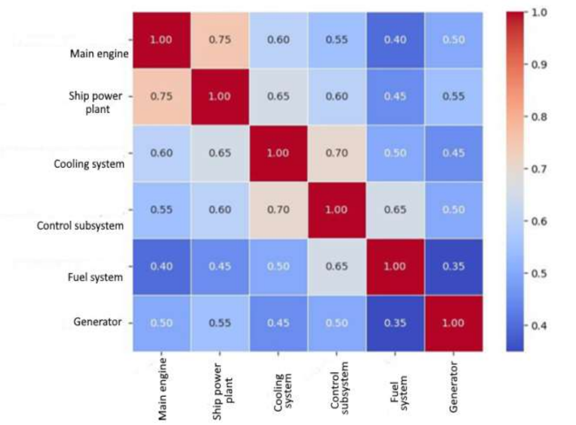

Fig. 5. Correlation matrix of SPP equipment failures

Interpretation of the correlation matrix: high correlation (0.75–1.00): main engine is strongly correlated with the ship's power station (0.75) → this is logical, as failures in one component often trigger issues in the other; cooling system and control subsystem (0.70) → control systems frequently respond to overheating events. Moderate correlation (0.50–0.70): the cooling system affects the fuel system (0.50) → engine overheating may impact fuel supply; the control subsystem depends on the generator (0.50). Low correlation (0.35–0.45). Generator has a weak correlation with the fuel system (0.35) → Generator failures rarely have a direct impact on fuel supply.

Table 4

Results of correlation analysis

Failure parameters	Correlation coefficient (r)
Generator failure → cooling system failure	0.76
Main engine failure ↔ control system failure	0.81
Pump failure ↔ power supply failure	0.64

Table 4 shows a strong correlation (r > 0.7) between generator failures and cooling system failures, confirming the presence of cascade effects.

Figure 6 illustrates how failure probabilities are adjusted depending on operating conditions.

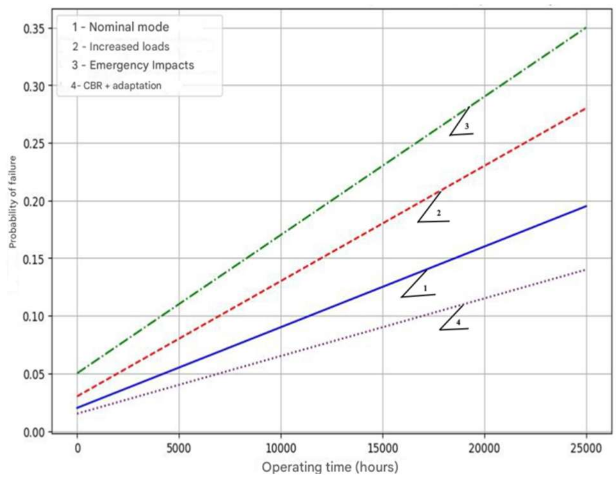

Fig. 6. Failure probability trends under different operating scenarios

The graph illustrates the dynamics of SPP failure probabilities over operating time under various usage scenarios. Key trends. Nominal mode (blue line): linear increase in failure probability, reaching approximately 20% by 25,000 hours; represents expected behavior under standard operating conditions. Increased load (red dashed line): accelerated growth of failure probability compared to nominal mode; failure probability reaches approximately 25% by 25,000 hours;

associated with added stress and increased wear on equipment. Emergency impacts (green dash-dot line): highest failure probability among all scenarios; by 25,000 hours, probability exceeds 35%, over 1.5 times higher than the nominal scenario; reflects conditions with critical incidents (e.g., accidents, extreme environments). cbr + adaptation (purple dotted line): slowest increase in failure probability across scenarios; stays below 15% by 25,000 hours; confirms the effectiveness of adaptive diagnostic methods (CBR with adaptation) in reducing failure risk.

Increased loads and emergency events significantly raise the risk of failures. Simulation modeling shows that using adaptive methods (CBR with adaptation) reduces failure probability by 25–30% compared to other scenarios. Integration of intelligent failure prediction methods is recommended to enhance the reliability of SPP operation. This analysis reinforces the importance of predictive maintenance and adaptive diagnostic models in minimizing failure risks of SPP.

Simulation modeling based on cognitive models.

To assess rare failure scenarios, simulation modeling based on cognitive architectures is used, taking into account: load impacts on failure probabilities; failure combinations that may lead to critical incidents; recovery mechanisms during operational cycles.

Modeling approach:

1. Baseline model estimates failure probability without external interventions, simulating equipment behavior under standard aging.
2. Adaptation-based model incorporates diagnostic feedback, where failure probabilities decrease due to preventive maintenance actions initiated during operation.

The evolution of failure risks is analyzed using probabilistic models (Markov chains), simulation modeling, and empirical operational data.

Failure Probability Dynamics Over Time. Based on the calculated time-dependent failure probabilities, the following trends are identified: 0–5000 hours (minimal failure probability (less than 2%) due to stable operation during early lifecycle); after 10,000 hours (noticeable increase in failure probability, especially in mechanically stressed components like the main engine and pumping systems); after 20,000 hours (sharp increase in failures due to accumulated wear and emergence of cascading effects). 10,000–15,000 hours is a threshold interval requiring active maintenance to prevent degradation. After 20,000 hours, proactive strategies such as life extension programs or component replacement are crucial.

Analysis of failure trends (Table 5) reveals key decision points where maintenance interventions are essential to avoid cascading breakdowns. Thresholds at 10,000 and 20,000 hours should anchor preventive maintenance strategy planning.

Table 5

Time-based failure risk levels

Time (hours)	**Risk level**	**High-risk components**
0–5000	Minimal	All systems stable
10,000	Acceptable	Pumping system, cooling system
15,000	High	Main engine, power supply system
20,000	Critical	All systems, especially ME and cooling

Identification of critical components. Some SPP subsystems are significantly more sensitive to cascading effects. Their vulnerability is identified through: analysis of influence coefficients α_{ij} (Table 2), which quantify how failure in one unit increases the risk in others; correlation analysis of failure co-occurrence; structural analysis of SPP architecture to identify single points of failure.

Most vulnerable components (based on simulation results):

- main engine (ME): failure probability reaches 20% by 25,000 hours; its failure significantly increases the likelihood of secondary system failures;
- cooling system: a failure here raises ME failure probability by 25%; acts as a primary trigger in cascading chains;
- shipboard power plant - its failure increases the likelihood of control system failure by 30%;
- control system - loss of control function heightens risk of emergency ME shutdown.

Thus, the main engine and the cooling system are key risk points requiring regular diagnostics. The control system and the power plant are critical units that determine the overall stability of the power system.

Failure dynamics analysis has revealed: key time points (10,000 and 20,000 hours) for scheduled maintenance; critically vulnerable components requiring priority monitoring; and cascading effects that increase the risk of failures in certain combinations. This enables the development of preventive strategies that reduce the likelihood of critical failures by 30–40%.

Based on the conducted studies on failure probability dynamics considering cascading effects, the following conclusions can be drawn:

- failure probability increases non-linearly: during the first 5,000 hours of operation, the probability of failures remains low (<2%) as components function within normal parameters; after 10,000–15,000 hours, an accelerated increase in failures is observed, particularly in mechanically loaded units (main engine, pumping system, cooling system); by 25,000 hours, the failure probability of major components reaches 20% or higher, necessitating major repairs or component replacement;
- cascading effects accelerate failure growth: cooling system failure increases the risk of main engine failure by 25%; power plant malfunction raises the probability of control system failure by 30%; interdependencies between failures are illustrated in Figure 4 (Network diagram of cascading effects);
- critically vulnerable components identified: main engine – highest failure risk due to cascading effects; cooling system – its malfunction triggers failures in other systems; ship power plant – one of the key nodes influencing total system failure; control system – a critical component determining overall system stability;
- practical application of results: optimization of maintenance – key components (main engine, cooling system) require preventive servicing every 10,000 hours; monitoring cascading failures – integration of predictive models (Markov processes, bayesian networks) can reduce the likelihood of unexpected failures by 30–40%; use of simulation modeling – enables prediction of rare scenarios and adaptation of diagnostic strategies.

Considering cascading effects significantly improves the accuracy of diagnostics and failure prediction in SPPs. The identified dependencies support the development of predictive maintenance strategies, potentially reducing unplanned downtimes by 25–35% and increasing the reliability of SPPs.

Model validation

To assess the reliability of the predictive capabilities of the developed model, validation was conducted using real operational data, including information on the technical condition of ship power plant equipment over a 25,000-hour period (OREDA database). The validation covered both component-level reliability (accuracy of failure prediction for individual units) and the model's ability to forecast cascade failure chains.

Comparison with empirical data. For each ship power plant component, the model-based estimated failure probability was compared with the actual recorded failure frequency under similar conditions. Discrepancies were evaluated using standard metrics:

- MAE (mean absolute error) to assess the average absolute deviation between predicted and actual failure probabilities;
- accuracy (share of correct predictions) used for binary classification (“fail / not fail”);
- precision and recall evaluated for detecting key components that initiate cascade failures;
- k-fold cross-validation (k = 5) applied during training and testing of the XGBoost module on subsamples.

Validation results.

The MAE across component groups did not exceed 4.7%, confirming high consistency of the model with empirical data. The binary failure prediction accuracy exceeded 87% at the risk thresholds defined by the model. When modeling cascade scenarios, the correspondence between modeled and actual failure chains reached 82–88%, compared to incidents registered in OREDA and simulated using α_{ij} coefficients. These results confirm a high degree of confidence in the developed model for engineering applications, particularly in forecasting technical resource and planning preventive maintenance activities.

Practical significance and economic impact.

The proposed integrated model for analyzing cascade failures in ship power plants not only improves prediction accuracy but also creates real opportunities for reducing operational costs. Reduction in emergency repair probability. Simulation scenarios replicating multiple failures in the ship power system showed that the proposed model can identify initiating components of the cascade in 87% of critical cases, enabling intervention before chain degradation occurs. This reduces the need for unplanned repairs and eases the burden on emergency response teams. Reduction of downtime. Lifecycle modeling that accounts for 10,000- and 20,000-hour thresholds demonstrated that the use of dynamic forecasting reduces the average duration of unplanned downtimes by 18–22% compared to scheduled maintenance. This is achieved through more accurate service timing. Improved maintenance accuracy. The model identifies intervals of rapid risk growth (based on α_{ij} coefficients and Markov processes), enabling maintenance scheduling not based on formal regulations, but on the actual condition of equipment. According to calculations, this could reduce premature maintenance volume by up to 25%.

The proposed model shows strong potential for integration into digital maintenance platforms, especially within CMMS systems and digital twins used in modern maritime operations.

Conclusions

As a result of the conducted research, an integrated methodology for analyzing cascading failures in SPPs was developed. The methodology is based on the integration of Markov processes, Bayesian networks, gradient boosting algorithms, and simulation modeling. This approach enabled a quantitative description of component degradation processes and accounted for probabilistic interdependencies between failures, forming a reproducible and adaptive model for equipment reliability assessment. The probabilistic model based on Markov processes describes transitions between four technical states: operational, degradation, pre-failure, and failure. Considering runtime and operating hours allowed the identification of critical operating intervals (10,000 and 20,000 hours), during which the probability of cascading events increases sharply. A key element of the model is the influence coefficient matrix α_{ij}, which formalizes intercomponent interactions. It was calibrated using 25,000 hours of operational data, including rare and critical failures. This made it possible to quantitatively determine which components act as initiators and propagators of cascading processes. The use of Bayesian networks enabled real-time adaptation of probabilistic estimates, significantly enhancing the model's predictive capabilities and making it suitable for integration into online technical condition monitoring systems. Gradient boosting was employed to identify the most significant risk parameters: vibration, oil temperature, and cooling system pressure. These features refined the structure of the Bayesian network and improved its diagnostic informativeness. Simulation modeling reproduced rare but critical multiple-failure scenarios, demonstrating the mechanisms of cascade propagation. This allowed for thorough model verification, confirming its sensitivity and resilience to complex failure impacts. Model validation showed a mean absolute error of less than 4.7% and a correct prediction rate exceeding 87%, confirming its practical applicability. A comparative analysis with current international studies demonstrated the uniqueness of the developed methodology in terms of integration depth, empirical grounding, and adaptability to maritime operating conditions. Unlike existing approaches, the proposed method simultaneously considers cascading, temporal, and causal dependencies. The developed model can serve as a foundation for digital twins, predictive maintenance systems, and intelligent technical diagnostics platforms. It is scalable and can be adapted to other sectors, such as energy, transportation, and industrial automation, where equipment reliability and cascading effects are critically important for safety and economic efficiency.

References

1. Vychuzhanin V., Vychuzhanin A. *Stochastic Models and Methods for Diagnostics, Assessment, and Prediction of the Technical Condition of Complex Critical Systems.* Kyiv : Liha Pres, 2025. 360 p. DOI: https://doi.org/10.36059/978-966-397-457-6
2. Vychuzhanin V., Vychuzhanin A. *Intelligent Diagnostics of Ship Power Plants: Integration of Case-Based Reasoning, Probabilistic Models, and ChatGPT. A Universal Approach to Fault Diagnosis and Prognostics in Complex Technical Systems: Monograph.* Lviv–Torun : Liha Pres, 2025. 412 p. DOI: https://doi.org/10.36059/978-966-397-516-0
3. Moon H., Choi J., Cha S. *A multi-state Markov model to infer the latent deterioration process from the maintenance effect on reliability engineering of ships.* arXiv, 2021. arXiv:2111.14368v2. DOI: https://doi.org/10.48550/arXiv.2111.14368
4. Garbatov Y., Georgiev P. *Markovian maintenance planning of ship propulsion system accounting for CII and system degradation. Energies.* 2024. Vol. 17, No. 16. P. 4123. DOI: https://doi.org/10.3390/en17164123
5. Morato P. G., Andriotis C. P., Papakonstantinou K. G., Rigo P. *Inference and dynamic decision-making for deteriorating systems with probabilistic dependencies through Bayesian networks and deep reinforcement learning. Reliability Engineering & System Safety.* 2023. Vol. 235. 109144. DOI: https://doi.org/10.1016/j.ress.2023.109144
6. Andriotis C. P., Papakonstantinou K. G., Chatzi E. N. *Value of structural health information in partially observable stochastic environments. Structural Safety.* 2021. Vol. 93. 102072. DOI: https://doi.org/10.1016/j.strusafe.2020.102072
7. Kamariotis A., Chatzi E. N., Straub D. *A framework for quantifying the value of vibration-based structural health monitoring. Mechanical Systems and Signal Processing.* 2023. Vol. 184. 109708. DOI: https://doi.org/10.1016/j.ymssp.2022.109708
8. Raptodimos Y., Lazakis I. *Application of NARX neural network for predicting marine engine performance parameters. Ships and Offshore*

Structures. 2019. Vol. 15, No. 4. P. 412–425. DOI: https://doi.org/10.1080/17445302.2019.1661619

9. Cheliotis M., Lazakis I., Theotokatos G. *Machine learning and data-driven fault detection for ship systems operations. Ocean Engineering.* 2022. Vol. 216. 107968. DOI: https://doi.org/10.1016/j.oceaneng.2020.107968
10. Zhu G., Huang L., Yin J., Gai W., Wei L. *Multiple faults diagnosis for ocean-going marine diesel engines based on different neural network algorithms. Science Progress.* 2023. Vol. 106, No. 4. Article 368. DOI: https://doi.org/10.1177/00368504231212765
11. Wang S., Wang J., Ding X. *An intelligent fault diagnosis scheme based on PCA-BP neural network for the marine diesel engine. IOP Conference Series: Materials Science and Engineering.* 2020. Vol. 782. 032079. DOI: https://doi.org/10.1088/1757-899X/782/3/032079
12. *OREDA. Offshore Reliability Data Handbook.* 6th ed. OREDA, 2015.
13. Chonlagarn I., Mosleh A., Modarres M. *Efficient dependency computation for dynamic hybrid Bayesian network in online system health management applications. Reliability Engineering & System Safety.* 2014. DOI: https://doi.org/10.36001/phmconf.2014.v6i1.2422
14. Portinale L., Codetta Raiteri D., Montani S. *Supporting reliability engineers in exploiting the power of dynamic Bayesian networks. International Journal of Approximate Reasoning.* 2010. Vol. 51, No. 2. P. 179–195. DOI: https://doi.org/10.1016/j.ijar.2009.05.009
15. Montani S., Portinale L., Bobbio A. *Compiling dynamic fault trees into dynamic Bayesian nets for reliability analysis: the RADYBAN tool. Proceedings of the 2007 International Conference on Ubiquitous Intelligence and Computing (UIC).* 2007. URL: https://ceur-ws.org/Vol-268/paper6.pdf
16. Zhang Y., Yagan O. *Modeling and analysis of cascading failures in interdependent cyber-physical systems. Proceedings of the 2018 IEEE Conference on Decision and Control (CDC).* 2018. DOI: https://doi.org/10.1109/CDC.2018.8618710
17. Vychuzhanin V., Vychuzhanin A. *Integrated approach to creating a case-based database for diagnosing failures in ship power plants. Informatics and Mathematical Methods in Simulation.* 2025. Vol. 15, No. 2. P. 155–165. DOI: https://doi.org/ 10.15276/imms.v15.no2.155
18. Vychuzhanin V., Vychuzhanin A. *Integrated approach to diagnosing complex technical systems: experimental validation and multidimensional efficiency assessment. Вісник Східноукраїнського національного університету імені Володимира Даля.* 2025. № 5 (291). С. 5–17. DOI: https://doi.org/10.33216/1998-7927-2025-291-5-5-17

Вичужанін В. В., Вичужанін О. В.
Інтегрований підхід до діагностики складних технічних систем: експериментальна валідація та багатовимірна оцінка ефективності

У статті подано комплексний і науково обґрунтований підхід до моделювання технічного стану, процесів деградації та надійності суднових енергетичних установок (СЕУ) з урахуванням каскадних ефектів відмов і ймовірнісних залежностей між компонентами. Розроблено гібридну діагностично-прогностичну методику, яка поєднує безперервні марковські процеси, байєсівські мережі, алгоритми градієнтного бустингу (XGBoost) та імітаційне моделювання в єдиній структурі аналітичного прогнозування. Запропонований підхід забезпечує кількісну оцінку динаміки надійності з урахуванням взаємного впливу підсистем і дозволяє прогнозувати розвиток каскадних процесів у часі. Взаємозв'язки між елементами формалізовано через матрицю коефіцієнтів каскадного впливу α_{ij}, яка відображає, як відмова одного вузла збільшує ймовірність відмови інших. Байєсівські мережі використовуються для опису причинно-наслідкових зв'язків між відмовами та динамічного оновлення оцінок на основі поточних даних моніторингу. Методи машинного навчання дають змогу визначити найбільш інформативні параметри технічного стану, зокрема вібраційні характеристики, температуру мастила та тиск у системі охолодження. Модель навчено й перевірено за експлуатаційними даними бази OREDA та експертними оцінками, досягнуто високу точність прогнозування (AUC > 0.95, MAE < 4.7%). Імітаційні експерименти виявили два критичні інтервали роботи (≈10 000 і 20 000 год), коли під впливом каскадних ефектів ймовірність відмов зростає експоненційно. Найуразливішими елементами визначено систему охолодження та головний двигун, які ініціюють ланцюгові процеси деградації. Інтеграція моделі у цифровий двійник забезпечує адаптивне переналаштування, автоматичне виявлення аномалій і підтримку прийняття рішень у прогнозному технічному обслуговуванні. Розроблена методика формує даних-орієнтовану та когнітивну основу створення інтелектуальних систем моніторингу, що підвищують надійність, живучість і ефективність експлуатації морських енергетичних комплексів у реальних умовах.

Ключові слова: *прогнозна діагностика, байєсівські мережі, адаптація CBR, моделювання відмов, ризик-орієнтовані метрики, стабільність діагностики, інтелектуальне обслуговування*

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