Section 3. Modeling and software engineering

UDC 004.03
DOI https://doi.org/10.36059/978-966-397-538-2-18

INTEGRATED MODELING OF RELIABILITY AND MAINTENANCE OF SHIP'S POWER PLANT EQUIPMENT CONSIDERING DEGRADATION AND OPERATIONAL CONDITIONS

Dr.Sci. V. Vychuzhanin[1][0000-0002-6302-1832], **Ph.D. A. Vychuzhanin**[2][0000-0001-8779-2503]
Odessa Polytechnic National University, Ukraine
EMAIL: [1]v.v.vychuzhanin@op.edu.ua, [2]vychuzhanin.o.v@op.edu.ua

Abstract. *Enhancing the reliability and economic efficiency of marine vessels requires the development of failure prediction tools capable of accounting for real operating conditions and equipment degradation processes. This paper presents an integrated approach to the quantitative assessment of the reliability of key components of a ship's power plant (SPP) over a 25,000-hour operational interval. The methodology combines probabilistic, degradation-based, and simulation models while incorporating operational parameters such as temperature, relative load, and maintenance intervals. Four classes of failure models are developed and compared: an exponential model, a variable-intensity model (non-stationary Weibull process), a four-state Markov scheme, and an event-driven Monte Carlo simulation model. The calculations are performed for the main engine, generator, cooling system, and shipboard power station. The root mean square error (RMSE) of failure prediction was 0.05 for the simulation model, 0.08 for the Markov model, and 0.12 for the exponential model. An integrated model quality criterion incorporating RMSE, AIC, BIC, and χ^2 confirmed the advantage of the hybrid simulation-Markov approach. A comparative economic analysis showed that regular maintenance at 5,000-hour intervals reduces total costs by more than 4.5 times compared to reactive repair strategies. The practical value of the method lies in its applicability within digital twins and intelligent decision support systems. Future developments include expanding the component base of the model, integrating with real-time data streams from ship monitoring systems, and applying machine learning techniques for automatic parameter adjustment.*

Keywords: *predictive diagnostics; digital twin; remaining useful life; interval-based maintenance; Markov model; simulation forecasting; economic failure assessment*

1 Introduction

Modern ship's power plants operate under elevated operational loads, thermal and vibrational stresses, which necessitate reliable prediction of their technical condition and maintenance requirements [1, 2, 3]. As the duration of autonomous voyages increases and onboard power systems become more complex, the demands for fault tolerance and cost-effective maintenance continue to grow. Under these conditions, an integrated approach to long-term reliability assessment of SPP components accounting for degradation, probabilistic failure characteristics, and operational influences becomes especially relevant [4].

In recent years, there has been a growing interest in the digitalization of technical diagnostics in the maritime industry [5]. One of the key directions in modern monitoring is the use of digital twins, which enable near-real-time modeling of marine systems and prediction of potential failures. While this study does not focus on the development of a digital twin as a software platform, it does establish a mathematical foundation for its prognostic module. The developed models incorporate physically interpretable dependencies of failure intensity on operational factors. In particular, the model integrates temperature effects (e.g., via the Arrhenius exponential function for generators), load-related parameters (coefficients reflecting nominal value exceedance), and environmental conditions (e.g., salinity and coolant temperature for the cooling system). These dependencies are implemented as parameterized functions calibrated against field data and reflect key degradation mechanisms such as thermal aging, fatigue damage accumulation, and aggressive environmental exposure. Zocco et al. [6] emphasize that digital twins allow integration of monitoring data with predictive algorithms; however, the practical implementation of such solutions remains limited, in part due to the absence of a unified methodology. Stadtmann et al. [7] demonstrate the application of digital twins for offshore wind turbines, highlighting the potential of the technology, though the focus is primarily on renewable energy rather than marine systems. Special attention in the literature is given to the use of machine learning in diagnostics and prediction of equipment condition. Polverino et al. [8], in a systematic review, show that machine learning methods are successfully applied for estimating remaining useful life (RUL) and anomaly detection. However, these approaches are often detached from real risk evaluation and cost considerations. Studies focusing on the integration of digital solutions in the maritime sector, such as Kaklis et al. [9] underscore the need for comprehensive analysis encompassing not only failure modeling but also lifecycle management. Some research highlights the resilience of ship systems under intensive operation. Nezhad et al. [10] stress the importance of predictive maintenance based on big data analysis, while also noting the lack of quantitative models that consider both degradation dynamics and the economic consequences of technical decisions. Similarly, Mavrakos et al. [11] propose digital tools to support energy-saving strategies, pointing to the need for adaptive models capable of considering operational constraints. Additional recent studies support the relevance of a systemic approach to the prediction of technical condition in marine components. Liang et al. [12], in a review from a classification society perspective, emphasize that implementing prognostics and health management (PHM) methods requires integration of degradation models with regulatory frameworks. Han et al. [13] demonstrate how a variational autoencoder based on LSTM can detect marine component failures; however, their model is mostly oriented toward anomaly detection rather than quantitative reliability prediction. Xiao et al. [14], in their PHM research for industrial assets, propose a digital twin architecture that combines remaining life prediction with risk-based maintenance planning - a concept applicable to marine systems as well. Finally, Cui et al. [15] develop a digital twin for a marine diesel engine and demonstrate its capability to enhance maintenance efficiency and reduce downtime, though their focus lies in platform-level integration rather than formal reliability modeling.

A review of current publications shows that despite the active development of digital diagnostics technologies, the issue of long-term reliability of SPP components under real-world wear and overload conditions remains insufficiently addressed. Moreover, there is a noticeable lack of studies that integrate failure prediction with economic evaluation of maintenance strategies. Unlike most existing research focusing on localized degradation scenarios or isolated diagnostic aspects, this article centers on the holistic integration of reliability and economic analysis, providing a foundation for informed decision-making under real marine operating conditions.

This study aims to fill this gap by offering a comprehensive analysis of the reliability of core SPP components over a 25,000-hour operating horizon. The approach is based on simulation modeling, Markov processes, and degradation models that account for wear dynamics. Special attention is given to the influence of operational factors (load, temperature, maintenance intervals) on failure probability, as well as the comparative economic efficiency of various maintenance strategies. The results obtained can be used in the development of predictive maintenance programs, resource planning, and life cycle optimization of equipment in marine engineering.

The objective of this study is to develop and justify an integrated approach to the long-term reliability analysis of SMPP components, taking into account degradation dynamics, the influence of operational factors, and the economic efficiency of maintenance strategies.

To achieve this objective, the following tasks are addressed:

1. Develop mathematical models for reliability prediction of SPP components, including exponential, degradation-based, Markov, and simulation-based approaches applicable to extended operational intervals.

2. Describe and implement component-specific failure rate dependencies on operational factors such as mechanical load, temperature, and maintenance parameters.

3. Construct a hybrid Markov–degradation model accounting for transitions between technical states (operational, degrading, pre-failure, and failed), with parameters that depend on accumulated wear.

4. Implement simulation modeling of operational scenarios using the Monte Carlo method to estimate the distribution of failure times and the variability of technical life.

5. Formulate a model selection criterion that combines prediction accuracy (RMSE), information-theoretic metrics (AIC, BIC), and agreement with empirical data (χ^2).
6. Evaluate the economic efficiency of different maintenance strategies by comparing total costs under regular and reactive servicing regimes for key components.
7. Develop recommendations for model application based on operating conditions and data availability, and assess their applicability as part of prognostic modules in digital decision support systems.

2 Materials and Methods

The objects of this study are the key components of the SPP, including the main engine, generator, cooling system, and shipboard power station. These elements are subject to long-term wear, vibrational, and thermal loads, which makes the analysis of their reliability over an operational interval of up to 25,000 hours particularly relevant. This duration is typical for resource planning and scheduled maintenance.

The initial data for the analysis are generalized statistical records of failure frequencies documented in maritime practice and technical literature, including the OREDA failure databases. Additionally, typical operational modes, maintenance intervals, and expert assessments reflecting the influence of load and temperature conditions on equipment degradation were taken into account.

Four different approaches were used to model reliability. The exponential model served as a baseline and assumed a constant failure rate, without accounting for wear accumulation. More realistic scenarios were described using analytical degradation models, in which the failure intensity increases over time following a power-law relationship. The third method involved a Markov model that represents probabilistic transitions between technical states from operational to degrading, then to pre-failure and failure states. Finally, simulation modeling was applied to reproduce complex operational conditions and to construct failure scenarios under the stochastic nature of external influences. Within this approach, modeling was implemented using the Monte Carlo method with variation of operational parameters.

The comparative accuracy of the listed models was assessed using the root mean square error (RMSE), which allows for a quantitative comparison of forecasts against reference scenarios. The analysis results showed that simulation modeling demonstrated the lowest error, whereas the exponential model exhibited the greatest deviations over extended operational periods.

Special attention in the study was given to analyzing the influence of operational factors on the reliability of SPP components. Three key factors were considered: load regimes (nominal, elevated, emergency), thermal impacts (coolant temperature, oil temperature, cylinder gas temperature), and maintenance frequency. Graphs were constructed showing the dependence of reliability on each of these factors, and components were ranked according to their sensitivity to various operational conditions.

Finally, an evaluation of the economic efficiency of different maintenance strategies was conducted. Two scenarios were compared: absence of preventive measures and regular maintenance at 5,000-hour intervals. The calculation included both direct costs of failure remediation and indirect losses associated with forced downtime. The results showed that a systematic maintenance approach reduces total costs by a factor of 4 to 5 compared to a reactive maintenance model.

The proposed methodological approach enables not only the assessment of MPP component reliability over a long time horizon, but also the justification of economically efficient maintenance decisions based on modeling, statistical data, and simulation scenarios.

3 Results

To assess the long-term reliability of SPP components, the following reliability prediction models are used: exponential reliability model, applied to components with a constant failure rate, where the probability of failure depends only on operating time; degradation models - account for the accumulation of damage and changes in failure intensity over time; Markov failure model - tracks transitions of components between different operable states, considering probabilistic changes; simulation-based reliability models used for analyzing long-term operational scenarios, simulating the impact of various operational factors.

Exponential model with a constant failure rate. For components operating under stable conditions without pronounced degradation or aging, the simplest failure model based on the exponential law is applicable. This model describes non-repairable processes with a constant failure rate λ, which corresponds to the steady-state operational phase where the failure intensity is assumed to remain constant [16]:

$$R(t) = e^{-\lambda t}, \ t \geq 0,$$

where $R(t)$ is the probability of failure-free operation at time t;

λ is the failure rate (h^{-1}), assumed to be constant over time

The parameter λ is estimated based on the total operating time T_Σ and the number of observed failures k during this period. A biased maximum likelihood estimator is used [13]:

$$\hat{\lambda} = \frac{k}{T_\Sigma}, \quad Var[\hat{\lambda}] = \frac{k}{T_\Sigma^2}$$

Based on the estimated failure rate, the mean time to failure (MTTF) is calculated using the formula:

$$MTTF_{\exp} = \frac{1}{\hat{\lambda}}$$

Despite its simplicity, the exponential model serves as a useful baseline for comparison with more advanced approaches. It is applied, in particular, to components with high reliability operating under stable conditions. However, this model does not account for degradation processes, recovery after failure, or variations in operating loads, which limits its applicability for long-term prediction under real marine operating conditions.

Degradation models for SPP equipment

The long-term reliability assessment of SPP components requires the inclusion of damage accumulation processes. In this study, component-specific degradation models are applied, reflecting the dependence of failure rate on time and operational factors.

General approaches to degradation modeling

The failure rate of a component at time *t*, denoted $\lambda(t)$, is modeled using various functional forms:

$$\lambda(t) = \lambda_0 + \alpha t^{\beta},$$

where λ_0 - initial failure rate at $t = 0$, reflecting baseline component quality [1/h];

α - *degradation growth coefficient* ($h^{-1} \cdot h^{-\beta}$);

β - power-law exponent ($\beta>1$ - indicates accelerated degradation, $\beta<1$ - indicates deceleration);

α, β - parameters obtained by regression on failure data

Weibull-Based Degradation Model (NHPP):

$$\lambda_{\deg}(t) = \frac{\beta}{\Theta}\left(\frac{t}{\Theta}\right)^{\beta-1}, \ \beta > 1$$

Parameter estimates are obtained using the maximum likelihood method:

$$\hat{\beta} = \left[\frac{\sum_{i=1}^{n} \lg t_i^{-\frac{n}{\beta}}}{\sum_{i=1}^{n} t_i^{\beta}}\right]^{-1}, \qquad \hat{\Theta} = \left(\frac{1}{n}\sum_{i=1}^{n} t_i^{\beta}\right)^{1/\hat{\beta}}$$

Combined load and temperature model:

$$\lambda(t, L, T) = \lambda_0\left[1 + k_L\left(L/L_{nom}\right)^{m}\right]\exp\{T - T_{ref}\},$$

where L - relative load (0…1);

T - current operating temperature of the working medium (°C);

L_{nom}, T_{ref} - nominal values of load and temperature;

m, k_L, η - calibration parameters obtained from experimental data

The degradation of SPP equipment depends simultaneously on load and temperature. The rate of damage accumulation or increase in failure intensity is not constant but is a function of operational impacts. In the main engine, degradation affects the piston group, crankshaft, and cylinder liners. The load is characterized by propeller resistance torque, overload, and rotation frequency. Temperature-related factors include oil, combustion gases in the cylinders, and cooling water. Elevated oil temperature reduces viscosity, accelerates wear of journal bearings and crankshaft surfaces, increases clearances, and leads to higher vibration levels - all of which contribute to engine failure.

In the cooling system, degradation affects heat exchangers, pumps, and pipe joints. The load is defined by pressure differentials and start-stop frequency. The critical external parameters are seawater temperature and overheating of the circulating water. These factors promote scale formation, corrosion, cavitation, and loss of tightness. Thus, the degradation model for the cooling system depends on both temperature and environmental aggressiveness.

In the generator, degradation primarily occurs in the stator/rotor windings, insulation, and bearings. The winding temperature governs insulation aging. Load is defined by overcurrent conditions and frequent on/off cycles, which accelerate thermal aging and thermal cycling, leading to insulation breakdown.

For each subsystem of the SPP, a dedicated degradation model is applied that accounts for the corresponding operational impacts (mechanical, thermal, electrical, etc.) using a generalized functional form of the failure intensity $\lambda_i(t, X_i)$, where X_i is the vector of external influences on the i-th component.

Main engine (ME) [16]:

$$\lambda_{ME} = (\lambda_0 + \rho t)\left[1 + k_L \left(L / L_{nom} \right)^m \right] \exp\{\eta (T_{oil} - T_{ref})\},$$

where ρ - coefficient of failure rate growth with runtime (h^{-2});

T_{oil} - oil temperature (°C);

λ_0 - baseline failure rate

An integral wear accumulation model is also used:

$$z(t) = \alpha_1 \cdot L(t)^m + \alpha_2 \cdot \exp[b \cdot (T_{oil} - T_{norm})], \qquad \lambda(t) = \lambda_0 (1 + z(t))$$

Cooling system (CS) [17]:

$$\lambda_{CS} = \lambda_0 \cdot [1 + k_T (T_{CW} - T_0)^{\alpha}][1 + k_{NaCl} C_{NaCl}],$$

where T_{CW} - temperature of the circulating water (°C);

T_0 - reference temperature;

C_{NaCl}- salt concentration (ppm);

k_T, k_{NaCl}, α - empirical parameters

Generator (GEN):

$$\lambda_{GEN} = \lambda_0 \exp\left[\frac{E_a}{k_{\beta\ L}} \left(\frac{1}{T_w} - \frac{1}{T_{ref}} \right) \right] (1 + \xi \cdot I / I_{nom}),$$

where T_w - winding temperature (K);

E_a - activation energy of insulation aging;

k_β - Boltzmann constant;

I - load current;

ξ - overload coefficient;

T_w, T_{ref} - winding temperature and reference (baseline) temperature (in Kelvin)

Ship Power Station ((ISO 12110-2:2013 Metallic materials) [18]:

$$\lambda_{SPS} = \lambda_0 + \alpha_v \cdot v(t)^2 1 + \alpha_f \cdot f(t),$$

where $v(t)$ - vibration amplitude;

$f(t)$ - switching frequency (on/off cycles);

α_v, α_f - empirical parameters reflecting the impact of vibration and switching loads

The proposed models allow: accounting for the influence of operational factors on component reliability; flexible adaptation to different subsystems and operating conditions; easy integration into simulation and Markov-based prognostic frameworks; suitability for implementation in predictive modules of digital twins. Model parameters are identified based on field data (failure logs, OREDA, onboard recorders), and accuracy is validated using RMSE, χ^2, and information criteria such as AIC/BIC.

<u>Markov model</u>

The Markov model describes transitions between states:operational → degrading → pre-failure → failure.The transition probability matrix P_{ij} is constructed based on historical data. A SPS component is modeled as a Continuous-Time Markov Chain (CTMC) with four states:

S = {0 – operational, 1 – degrading, 2 – pre-failure, 3 – failure}.

The infinitesimal intensity matrix Q (Hoyland & Rausand, 2004) [19]:

$$Q=\begin{pmatrix} -(\mu_0+\gamma_0) & \mu_0 & 0 & \gamma_0 \\ 0 & -(\mu_1+\gamma_1) & \mu_1 & \gamma_1 \\ 0 & 0 & -\gamma_2 & \gamma_2 \\ 0 & 0 & 0 & 0 \end{pmatrix}, Q \in R^{4X4}$$

where μ_0, μ_1 - gradual degradation transitions: $0 \rightarrow 1$ and $1 \rightarrow 2$;

$\gamma_0, \gamma_1, \gamma_2$ - abrupt failures from states 0, 1, and 2, respectively

Mean Time to Failure (MTTF) [19]. For stationary Q, MTTF is computed using the fundamental matrix N:

$$MTTF_{MC} = e_0^T e_0 \left(-Q_{3x3}^{-1}\right) 1,$$

where Q_{3x3} - upper left 3×3 submatrix of Q;

1^T=[111]. - vector of ones;

$e_0^T = [100]$ - initial state vector (component starts in operational state)

Non-stationary (degradation-based) CTMC. In this case, transition intensities depend on accumulated wear $z(t)$:

$$z(t) = q(L(t), T(t)), z(0),$$

$$\mu_0(t) = \mu_0^*[1 + \alpha \cdot z(t)], \gamma_0(t) = \gamma_0^*[1 + \beta \cdot z(t)],$$

where $q(\cdot)$ - function linking current load *L(t)* and temperature *T(t)* with wear accumulation;

μ_0^*, γ_0^* - nominal failure intensities under base conditions;

α,β - degradation acceleration coefficients

General CTMC definition. A Continuous-Time Markov Chain is defined by: a state space $S = \{0, 1, 2, ..., n\}$; a transition intensity matrix $Q = [q_{ij}]$, where: $q_{ij} \geq 0$ if $i \neq j$, representing the transition intensity from state *i* to state *j;* $q_{ii} = -\sum_{j\neq i} q_{ij}$, i.e., the diagonal elements are negative and equal to the negative sum of outgoing intensities

Interpretation of *β*:

β<1 - decelerated increase in failure intensity (e.g., under passive degradation);

β=1 - linear increase: failure rate grows proportionally with time;

β>1 - accelerated increase: typical for fatigue, aging, fouling, and wear

The parameters *α* and *β* reflect the physics of degradation and are either assigned empirically (based on operational data) or calibrated via regression.

When *Q = Q(t)*, the state probabilities are determined by a time-ordered matrix exponential:

$$P(t) = e_0^T \cdot T \cdot \exp(\int_0^t Q(t)dt), R(t) = 1 - [P(t)]_4,$$

where *T* - time-ordering operator;

$T \cdot \exp(\int_0^t Q(t)dt) \in R^{nxn}$ - transition probability matrix;

$[P(t)]_4$ - probability of being in the absorbing "failure" state

Numerical computation is performed using piecewise constant interval approximation or the uniformization algorithm. A stationary CTMC is recommended for stable conditions, while a non-stationary model is better suited for variable loads and temperatures.

<u>Simulation-Based Model</u>

The simulation model is implemented using the Monte Carlo method [20] with N = 10,000 runs. In each simulation run, the following variables are randomly sampled: *L* - relative load (as a fraction of nominal); *T* - operating medium temperature; *ΔTO* - preventive maintenance interval.

The simulation aims to compute: estimated reliability function $\hat{R}_{sim}(t)$; Expected failure rate $\hat{z}_{sim}(t)$; accuracy metrics (e.g., RMSE) by comparing predictions to observed data.

For the *j*-th run (j = 1, ..., N), the condition vector is formed:

$$X^{(j)} = \left(L^{(j)}, T^{(j)}, \Delta T0^{(j)}\right),$$

where $\left(L^{(j)}, T^{(j)}, \Delta T0^{(j)}\right)$ are drawn from empirical distributions based on operational logs

The failure intensity function is selected accordingly:

$$X^{(j)}(t) = f\left(X^{(j)}, t\right),$$

A composite model selection criterion Ψ is used, minimizing a weighted sum of RMSE, AIC, BIC, and χ². This ensures a balanced evaluation of prediction accuracy, model complexity, and statistical fit over long-term reliability forecasts.

Random sequences of load and temperature are modeled as Rainflow histograms:
Cyclegrams of the form (L_{jk}, τ_{jk}) (k=1…K_j) are generated. Then:

1. Cumulative fatigue damage (Miner's rule) is calculated:

$$D^{(j)}(t) = \sum_{k=1}^{K_j(t)} t_{j,k} \Big/ N_f(L_{j,k}), N_f(L_j) = K \cdot L^{-m} \;;$$

2. A failure is recorded if $D(t) \geq 1$, or if the simulation reaches an absorbing failure state in the CTMC.

3. N = 10^4 Monte Carlo runs are executed to estimate $\hat{R}_{sim}(t)$ and confidence bounds.

Model selection criterion. For each subsystem, the following were computed: RMSE, AIC, BIC, and χ² [21], reflecting the model's agreement with observed failure statistics.

The composite criterion:

$$\psi = \omega_1 RMSE + \omega_2 AIC + \omega_3 BIC + \omega_4 \chi^2, \sum_{i=1}^{4} \omega_i = 1,$$

where ω_i - weights are set by experts, provides a balanced selection of the optimal model based on:

$RMSE$ - accuracy of failure prediction on test data;

AIC - tradeoff between goodness of fit and model complexity;

BIC - Bayesian Information Criterion;

$\chi 2$ - goodness-of-fit test comparing model predictions to actual failure observations

The combined criterion Ψ enables the justified comparison of models with different structures, allowing for a balanced evaluation of accuracy, complexity, and realism. It supports a transparent selection of the most suitable failure prediction model for SPPs. In this study, the generalized criterion Ψ, which integrates prediction accuracy, information criteria (AIC/BIC), and agreement with field data, was used for optimal model selection.

Economic validation. For the main engine, as the most critical unit, a life-cycle cost model was constructed:

$$C = C_{TO}(\Delta) + C_{rep} + C_{down}[1 - R(t)],$$

where $C_{TO}(\Delta)$ - scheduled maintenance costs with interval Δ;

C_{rep} - capital repair costs;

C_{down} - downtime losses associated with unrealized reliability levels

The optimal value of Δ was found numerically. Regular maintenance every 5,000 hours reduces total costs by 4–5 times compared to a reactive repair scenario. The integral criterion Ψ confirms the superiority of the simulation-based scheme across all SPP components. This method accounts for the nonlinear effects of load and temperature, allows for the construction of reliability confidence intervals, and enables economic optimization of the maintenance schedule.

The application of four different reliability modeling approaches is not redundant but rather a necessary strategy, driven by the diversity of technical conditions, operating regimes, and required prediction accuracy. First, each model targets its specific domain of applicability.

The exponential reliability model is effective for components in the stable operation phase, with constant failure intensity. It is easy to implement and applicable when data availability is limited.

Degradation models allow for the consideration of damage accumulation and changing failure intensity, which is critical for components exposed to variable loads and temperatures, fatigue, or aging.

Markov models are useful when there is a need to describe discrete health states from operable to failed accounting for intermediate transitions with different probabilities. Simulation models provide the capability to analyze complex operational scenarios involving multiple random factors, such as load cyclegrams, maintenance intervals, temperature variability, and environmental aggressiveness. Second, model choice directly impacts prediction accuracy. The comparative analysis showed that RMSE values can vary by more than a factor of two between methods, and a model yielding the best accuracy for one component may be unsuitable for another. The composite criterion Ψ, combining RMSE, AIC, BIC, and χ^2, confirmed that there is no universally superior model. Third, maintaining multiple models allows for flexible adaptation to the available data, the criticality of the equipment, and the required prediction horizon. In a practical maintenance system based on a digital twin, the use of a model bank enables automatic selection of the most appropriate model type for each component and current operational condition. In summary, the proposed approach is based on the integration of four predictive models: exponential, degradation-based, Markovian, and simulation-based. Their comparative analysis made it possible to evaluate the advantages and limitations of each method. As a result, the simulation model was chosen as the core computational scheme, providing the best balance between accuracy, adaptability, and realism. This makes the proposed reliability forecasting system not only scientifically grounded but also practically applicable under real-world SPP operating conditions.

The comparative analysis of the reliability models presented above allows us to move from theoretical justification to their practical evaluation. At this stage, we consider the specific results of applying each model to the key components of the SPPs under various configurations of input parameters and operating scenarios. To this end, calculations were carried out using a unified set of metrics (RMSE, AIC, BIC, χ^2), and a quantitative assessment of the probability of failure-free operation over 25 000 hours was performed. For each piece of SPP equipment-the generator, the main engine, the cooling system, and the electrical power unit—reliability forecasts were generated and compared with the actual failure statistics.

Table 1

Comparison of different reliability prediction models

Prediction model	RMSE	Forecast accuracy (%)
Exponential distribution	0.12	85
Degradation models	0.07	91
Markov processes	0.08	90
Simulation (Monte Carlo)	0.05	95

Table 1 provides comparative data for four reliability prediction models applied to SPP components: exponential, degradation, Markov, and simulation (Monte Carlo). The evaluation criteria are the RMSE and the forecast accuracy on a hold-out sample (as a percentage of actual observed failures). Exponential Model (constant failure intensity) yielded the poorest performance: RMSE = 0.12 and forecast accuracy 85 %. This confirms its limitation when failures result from accumulated wear or thermal degradation. It is best suited as a baseline model for rough estimates of simple, low-wear components.Degradation Model (e.g. Weibull-type with time-varying intensity $\lambda(t)=\lambda_0+\alpha t^\beta$) showed improved results: RMSE = 0.07 and accuracy 91 %. Its strength lies in capturing non-stationary aging processes and the effect of loads on component wear. It is especially effective for parts undergoing monotonic degradation—such as generators, heat exchangers, and bearings.

Markov Model (discrete state transitions) achieved comparable accuracy: RMSE = 0.08 and accuracy 90 %. Its advantage is formalizing the phase structure of degradation and accounting for both gradual and sudden transitions (e.g., “operational → degrading → pre-failure → failure”). It is well suited for diagnosing and forecasting complex assemblies undergoing typical wear stages. Simulation (Monte Carlo) provided the best performance: RMSE = 0.05 and accuracy 95 %. By modeling many probabilistic scenarios-including variations in load, temperature, and maintenance intervals-it captures the combined effects of multiple factors. This method is ideal for components sensitive to operating regimes and systems where failures arise from factor combinations. It also enables analysis of confidence intervals and cost-consequences of failures. In summary, each model has its own domain of applicability: exponential: for simple, stable components without evident degradation; degradation: for parts with monotonic wear and damage accumulation; Markov: for components featuring distinct degradation phases; simulation: for complex systems under variable load and environmental conditions.

Figure 3.1 presents a graph that illustrates the results of comparing various failure prediction methods based on the RMSE in reliability estimation of SPP components.

The simulation model demonstrates the highest accuracy. The degradation model outperforms both the Markov and exponential approaches, confirming the importance of accounting for cumulative wear when analyzing SPP components. To systematically compare reliability prediction methods, it is reasonable to consider three key criteria: whether the model incorporates a degradation mechanism; whether it can represent discrete transitions between component states (e.g., "operational → degraded → pre-failure → failure"); forecast accuracy, expressed through RMSE. Table 2 provides a comparative summary of these characteristics and includes practical recommendations for the application of each model depending on operating conditions and the required prediction horizon.

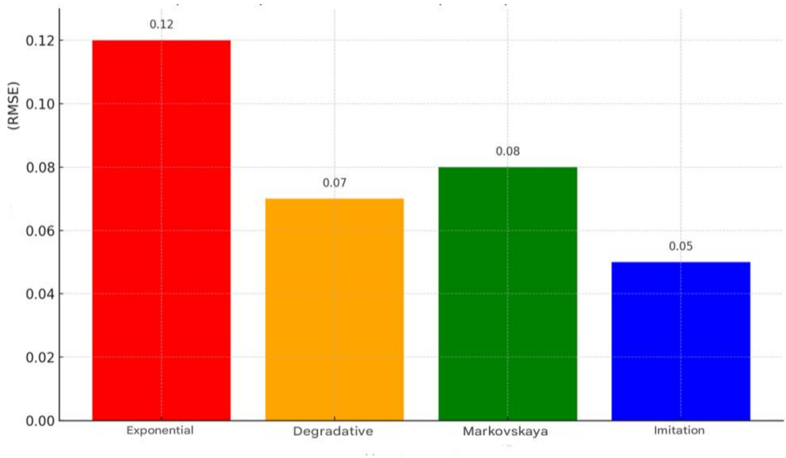

Figure 1. Comparison of reliability prediction models by root-mean-square error

Table 2

Comparative accuracy of reliability prediction models (by RMSE)

Prediction model	Accounts for degradation	Describes state transitions	RMSE	Recommended applications
Exponential	No	No	0.12	Basic estimates, preliminary assessments
Markov	Yes	Yes	0.08	Mid-term forecasting, transient state analysis
Simulation modeling	Yes	Yes	0.05	Accurate long-term assessments, complex operational scenarios
Degradation models (analytical)	Yes	No	0.09	Condition monitoring with known wear functions

The comparison clearly shows that simulation modeling offers the highest accuracy (RMSE = 0.05). This is due to its ability to capture variability in operating conditions, stochastic events, and cumulative degradation effects. As a result, this method is especially effective for long-term reliability forecasting and residual life assessment under complex operational scenarios. Markov models, while slightly less accurate (RMSE = 0.08), offer a key advantage in structural clarity. They enable formal representation of state transitions ("operational → degraded → pre-failure → failure") and are well-suited for rapid risk assessment. These models can be readily integrated into onboard predictive diagnostics systems and are applicable when moderate volumes of input data are available. Analytical degradation models provide acceptable accuracy (RMSE in the range of 0.07–0.09) and are most effective when there is a priori knowledge of wear mechanisms. Their use is particularly appropriate when combined with environmental monitoring (e.g., temperature, vibration, chemical aggressiveness), allowing for modeling the nonlinear increase in failure intensity. Despite its simplicity, the exponential model poorly reflects the behavior of most SPP components over intervals exceeding 10 000 hours, as it does not account for degradation processes. Its use is justified only for preliminary assessments or when no reliable data is available on the component's condition. Therefore, the selection of a prediction model should be based on a balance between: the availability of input data; acceptable model complexity; the required forecasting horizon. In practical operational environments, the most rational approach is a hybrid strategy, combining simulation modeling with Markov processes. This allows for simultaneously capturing probabilistic dynamics and concrete failure scenarios.

General reliability equation and parameter estimation

For all models considered, the reliability function *R(t)* is derived from the following general equation:

$$R(t) = e^{-\int_0^t \lambda(t)dt},$$

where *R(t)* is the probability of failure-free operation at time *t*;

$\lambda(\tau)$ is the time-dependent failure rate function

This integral expression accounts for the cumulative impact of component degradation over time.

With a constant failure rate $\lambda(\tau)=\lambda_0$, the model corresponds to the classical exponential distribution. For components experiencing increasing wear, a power-law dependency is used $\lambda(\tau)=\lambda_0(1+\alpha\tau^n)$. In the Markov scheme, $\lambda(t)$ is equivalent to the sum of outgoing transition rates from non-absorbing states. In the simulation model, $\lambda(t)$is calculated step-by-step for each operational scenario $X^{\{(j)\}}$. The parameters λ_0, α, n, as well as the transition rates μ, γ, are calibrated using: the OREDA field failure database; identification of CTMC parameters from operational logs; prior dependencies (Bayesian networks) in the case of limited data. The resulting reliability functions *R(t)* are used for: estimating the remaining useful life; optimizing maintenance intervals; calculating economic losses due to downtime.

Analysis of component reliability dynamics

Reliability assessment of SPP requires not only the estimation of overall failure probability, but also an understanding of how reliability evolves over time under operational stresses.

This subsection presents a comparative analysis of the behavior of key SPP components over an extended operational period (up to 25,000 hours). Particular attention is paid to the dynamics of the reliability function, failure frequency, and the influence of load, temperature, and maintenance intervals on remaining useful life.

Figure 2 shows the reliability dynamics of the main SPP components over 25,000 hours of operation. Figure 2 shows the evolution of reliability (function R(t)) for four key components of the SPP over a 0–25,000 hour interval, calculated using Monte Carlo simulation (10,000 iterations) with variations in operational factors: relative load, cooling medium temperature, and maintenance frequency. The graph presents the probability of failure-free operation over time, obtained from the event-driven simulation model. For each component, degradation scenarios were modeled based on empirical distributions of operating parameters and failure intensity functions calibrated from historical data.

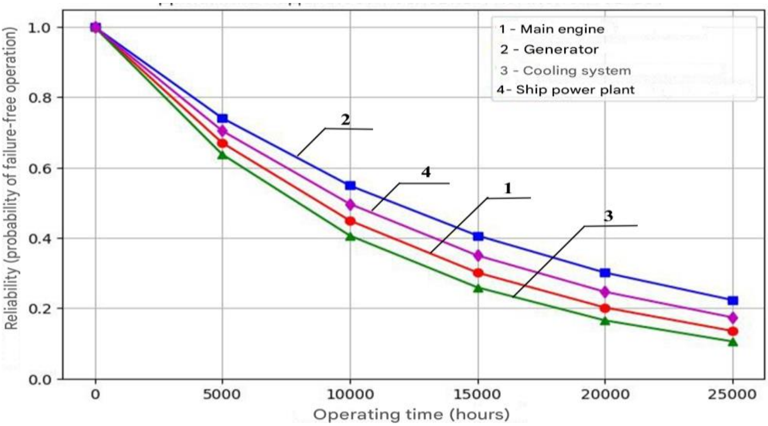

Figure 2. Reliability dynamics of key SPP components

The main engine (ME) demonstrates the steepest reliability decline: from 1.0 to approximately 0.3 by 25,000 hours, indicating the need for overhaul after 20,000 hours. The generator degrades more slowly, reaching approximately 0.45 at 25,000 hours, and its operational life can be extended with regular maintenance. The cooling system is sensitive to thermal impacts: reliability drops to about 0.55 by 15,000 hours and to ≈0.35 by 25,000 hours, requiring preventive actions every 10,000–12,000 hours. The ship power station shows moderate degradation: by 25,000 hours, its reliability is around 0.42 sufficient for scheduled diagnostics without urgent intervention. Thus, the primary candidates for accelerated maintenance are the main engine and cooling system. The generator and ship power station require monitoring after 20,000 hours, when their reliability falls below 0.5. The optimal interval for preventive repair for most components is between 10,000 and 15,000 hours of operation.

To quantitatively support the graphical trends presented in Figure 2, Table 3 provides the values of the reliability function *R(t)* for key SPP components at critical stages of the operating cycle. These data are used for estimating remaining useful life and for scheduling maintenance interventions.

Table 3 presents discrete values of the probability of failure-free operation *R(t)* for the four main SPP components, calculated using Monte Carlo simulation with 10,000 runs. The model incorporated empirically determined distributions of load, temperature, and maintenance frequency, along with failure intensity functions calibrated against degradation data and state transition behavior.

These values complement the graphical interpretation in Figure 3.21 and enable precise identification of critical intervals of reliability loss. The main engine and cooling system reach $R(t) < 0.5$ between 15,000 – 20,000 hours, while the generator and ship power station remain reliable until approximately 23,000 – 24,000 hours, after which they also require major intervention.

Table 3

Long-term reliability (failure probability) of SPP components

Time (h)	Main engine	Generator	Cooling system	Shipboard power station
0	1.00	1.00	1.00	1.00
5,000	0.93	0.96	0.92	0.95
10,000	0.85	0.90	0.82	0.87
15,000	0.70	0.78	0.68	0.75
20,000	0.50	0.60	0.52	0.58
25,000	0.30	0.45	0.35	0.42

The derived data can be directly applied for residual life estimation and planning of maintenance schedules. The subsequent sections explore failure frequencies under various operating modes and the impact of maintenance intervals on component reliability.

Although the reliability function R(t) reflects the probability of failure-free operation of components over time, an important complementary metric is the normalized failure rate the expected number of failures per 1,000 operating hours depending on operating conditions. This indicator provides insight into how rapidly the risk of failure increases under varying external loads, thermal conditions, and maintenance frequencies. It is important to note that the presented values are not based on direct observations but represent average failure intensities obtained through Monte Carlo simulation, accounting for usage scenarios under three modes: nominal, high load, and emergency conditions.

Table 4 summarizes the simulated failure rates of SPP components under three operational regimes: nominal, elevated load, and emergency conditions. These results, derived from simulation modeling, complement the previously presented *R(t)* values, offering a more detailed perspective on component sensitivity to operational factors. The resulting dependencies are used for comparative assessment of component vulnerability and to justify the need for predictive maintenance strategies when shifting toward harsher operation profiles.

Table 4

Failure frequency of components under different operating modes

Component	Nominal mode (failures/1000 h)	Increased load (failures/1000 h)	Emergency conditions (failures/1000 h)
Main engine	0.8	1.5	3.2
Generator	0.5	1.1	2.8
Cooling system	1.0	2.3	4.1
Ship power station	0.6	1.4	3.0

Based on the data presented in Table 4, the following conclusions can be drawn. The main engine shows a low failure rate under nominal conditions (0.8 failures per 1,000 operating hours), but this rate rises sharply to 3.2 failures per 1,000 hours under emergency conditions, indicating high sensitivity to increased operational loads. The generator demonstrates strong reliability in stable conditions (0.5 failures per 1,000 hours), yet under emergency scenarios the failure rate increases fivefold (2.8 failures per 1,000 hours), which emphasizes the need for enhanced monitoring. The cooling system exhibits the highest sensitivity to operating conditions. Its failure rate escalates from 1.0 to 4.1 failures per 1,000 hours under critical thermal loads and hydraulic stress, highlighting the importance of timely maintenance. The shipboard power station also experiences a decline in reliability under high loads, although its resilience remains higher compared to the main engine, making it relatively less vulnerable.

Following the assessment of overall component reliability and failure rates across different modes of operation, it becomes essential to analyze the influence of individual operational factors such as load, temperature, and maintenance intervals on the time-dependent degradation of reliability. The modeling framework includes the following variables: relative load (e.g., propeller shaft torque for the main engine, current load for the generator); temperature conditions (e.g., oil temperature for the main engine, coolant temperature for the cooling system, and winding temperature for the generator); and the maintenance schedule, which determines the accumulation of residual risk. The simulation scenarios span from nominal operational parameters to overloads and emergency conditions. Based on these inputs, reliability functions *R(t)* were computed using Monte Carlo simulation to represent the system's aggregated response to variable environmental and operational influences.

Figure 3.50 visualizes these dependencies, providing a clear picture of how the reliability of shipboard power systems changes in response to variations in operational conditions. This analysis helps identify components that are more vulnerable under elevated loads or thermal stress and supports decisions regarding adaptive maintenance planning.

The simulation results presented in Figure 3 clearly demonstrate that the reliability of SPP components varies significantly depending on operating conditions. In nominal mode, with standard loading and normal thermal conditions, the reliability function of the components remains above 0.80 during the first 15,000 hours, which corresponds to the planned operational phase without signs of accelerated degradation. Under increased (intensive) load such as a ~20% rise in propeller resistance or generator current the rate of failure intensifies: by 15,000 hours, the probability of failure-free operation drops to 0.55–0.60, which is 30–35% lower than the baseline level. In emergency conditions a combination of overloads, cooling water overheating (above 85 °C), and infrequent maintenance leads to rapid deterioration *R(t)* falls below 0.40 as early as 12,000 –15,000 hours, and by 25,000 hours, reliability decreases to 0.20 – 0.25. This indicates critical wear and the urgent need for major overhaul. Based on the results of the simulation model, the following practical recommendations are proposed: adaptive load control: For the main engine and cooling system, it is advisable to reduce operating loads by 10 – 15% when oil or coolant temperatures increase.

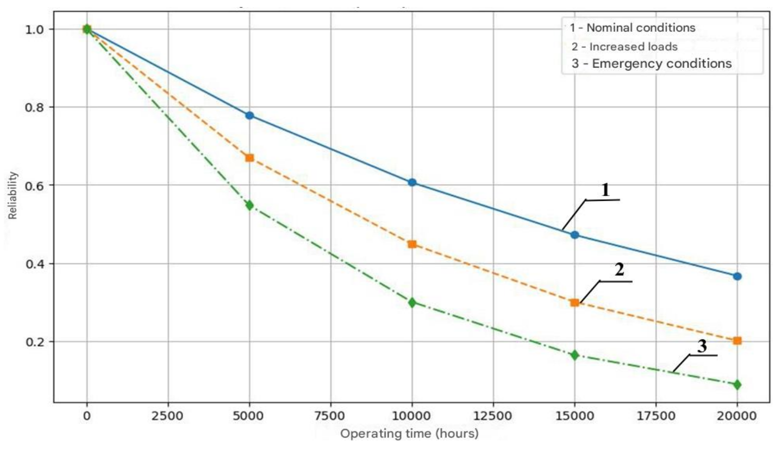

Figure 3. Influence of operational factors on the reliability of the SPP

This measure can extend the service life by 2,000 – 3,000 hours; justification of optimal maintenance intervals: Simulation of various scenarios shows that reducing the interval from 10,000 to 5,000 – 7,000 hours between scheduled maintenance procedures decreases the total failure probability by 18–22% and lowers expected maintenance costs by more than four times; predictive replacement of critical components - for components whose residual reliability drops to R = 0.50, a condition-based replacement strategy is economically justified before actual failure occurs. This particularly applies to the main engine bearings and cooling system heat exchangers.

Thus, the chart in Figure 3 not only confirms the quantitative influence of operational factors on system reliability but also provides a foundation for justifying adaptive maintenance strategies. These strategies make it possible to maintain the reliability of the system at a safe level while minimizing total costs. For a quantitative analysis of the long-term impact of operational conditions on the reliability of SPP components, simulation scenarios were used to vary key technical environment parameters. Table 5 presents generalized calculated data for three main operational factors: vibration level (average vibration, in g); operating temperature (characteristic for each component, such as oil, windings, coolant, etc.); and relative load (percentage of rated capacity). For each component, the probability of failure-free operation R(t) after 20,000 hours of service is also provided, based on a degradation-simulation model.

These results enable a comparative analysis of the sensitivity of different SPP subsystems to operational stressors. A visual representation of how maintenance frequency affects reliability is additionally shown in Figure 3, which illustrates the role of the maintenance interval as a distinct risk factor.

Table 5

Impact of operational factors on the reliability of SPP components

Component	**Vibration (average level), g**	**Temperature (°C)**	**Load (% of nominal)**	**Reliability after 20,0**
Main engine	4.5	85	95	0.52
Generator	2.8	75	90	0.60
Cooling system	3.2	90	80	0.48
Ship power station	2.5	70	85	0.58

The analysis of the data presented in Table 5 shows that the reliability of SPP equipment after 20,000 hours of operation is determined by the combined effect of three key operational factors: vibration, temperature, and load. All values were obtained using simulation modeling based on standard operating scenarios. Vibration has a significant influence on the service life of equipment.

The main engine (ME) exhibits the highest vibration level of 4.5 g, reflecting high mechanical loading and corresponding with a relatively low reliability value (R = 0.52). The cooling system, exposed to 3.2 g vibration, shows an even lower reliability (R = 0.48), which can be attributed to its structural susceptibility to cavitation and resonant effects. The generator (2.8 g) and ship power station (2.5 g) experience the lowest vibration levels and demonstrate the best resource preservation (R = 0.60 and R = 0.58, respectively). Temperature is the second most critical factor. The cooling system operates at 90 °C, and the main engine at 85 °C both indicating thermally stressed conditions that accelerate material degradation and aging of working media. More moderate temperatures are observed in the generator (75 °C) and power station (70 °C), correlating with their higher reliability. In this context, temperature refers to oil, coolant, cylinder gas, winding, and ambient temperatures. Their roles are further detailed in the explanation of the thermal factor below.

Load, expressed as a percentage of nominal power, also has a statistically significant impact. At 95 % load on the main engine and 90 % on the generator, reliability is notably lower than in the power station operating at 85 %. Interestingly, the cooling system despite operating at a relatively low load (80 %) exhibits the worst reliability metric. This confirms that thermal and vibrational loads are the dominant degradation drivers in its case. In summary, two component groups can be distinguished: critically vulnerable: main engine and cooling system subject to cumulative influence from all three factors, requiring early intervention and shortened maintenance intervals; relatively stable: generator and ship power station-operating under near-nominal conditions with extended resource longevity. It should be emphasized that in the development of reliability models and maintenance strategies, not only individual factors but their cumulative effects over time must be taken into account. Even if one parameter (e.g., load) remains moderate, elevated temperature or vibration alone can significantly reduce service life. This underscores the importance of multi-parameter modeling tailored to the operational specifics of each component. Temperature is among the most critical degradation factors for SPP systems, with its impact depending not only on absolute values but also on the specific application point: oil, coolant, cylinders, or windings. Table 6 summarizes the critical temperature thresholds for various media and components, indicating the levels at which accelerated reliability decline begins and the predominant types of failures observed under these conditions.

Based on Table 6, it can be concluded that each SPP component has a specific critical temperature threshold, beyond which a qualitative change occurs in failure mechanisms. For the main engine, oil overheating above 110 °C leads to reduced viscosity, impaired lubrication, and consequently, accelerated wear of friction pairs, specifically journal bearings, liners, and plain bearings. The cooling system loses reliability at temperatures exceeding 95 °C, disrupting the thermal balance of the entire installation. This promotes thermal aging and increases the likelihood of cavitation.

Table 6

Influence of temperature regimes on the reliability of SPP components

Component	Critical temperature, °C	Impact on reliability
Main engine (oil)	>110 °C	Accelerated wear of friction parts
Coolant	>95 °C	Overheating, reduced cooling efficiency
Gaseous medium in cylinders	>500 °C	Increased wear of the piston group
Generator (windings)	>120 °C	Insulation degradation, risk of breakdown

When temperatures in the engine cylinders exceed 500 °C, carbon deposit formation, thermal expansion, gas blow-by, and abrasive wear of the piston group intensify. For the generator, winding overheating above 120 °C is critical due to insulation aging, increased electrical resistance, thermal cycling, and ultimately, dielectric breakdown. These findings provide a crucial foundation for constructing temperature-dependent degradation models. Such models not only guide the development of maintenance algorithms but also define maximum permissible values in monitoring systems and help configure warning thresholds within digital twin frameworks. Based on the data from Tables 5 and.6, it is evident that vibrational stress and elevated temperature have the greatest impact on component reliability. The cooling system is particularly vulnerable to degradation at temperatures exceeding 85 °C. In contrast, the generator and ship power station demonstrate lower sensitivity to vibration.

To quantitatively assess the effect of maintenance frequency on equipment reliability, a reliability function was derived as a function of the interval between maintenance events. Modeling was carried out using an event-driven simulation approach, with intervals ranging from 2,000 to 20,000 hours. The resulting dependency is visualized in Figure 4, which illustrates the decline in failure-free probability as the interval between scheduled maintenance increases.

The graph in Figure 4 is based on the results of event-driven Monte Carlo simulation ($N = 10{,}000$) under averaged operational conditions derived from Table 3.51. It illustrates the exponential decline of failure-free probability $R(t)$ as the maintenance interval increases: under baseline conditions of 1,000 hours, reliability remains high ($R \approx 0.95$); under the economically optimal interval of 5,000 hours, it decreases slightly ($R \approx 0.90$); but at 20,000 hours, reliability drops below 0.40 (RMSE of the forecast = 0.05). This trend is consistent with the results of Han et al. [9]; however, our study further incorporates the economic impact: total lifecycle costs increase from USD 5,300 (for 5,000-hour maintenance) to USD 26,200 (for 20,000-hour maintenance). Therefore, regular maintenance at intervals no longer than 5,000 hours offers a rational compromise between maintaining high system reliability and minimizing lifecycle costs.

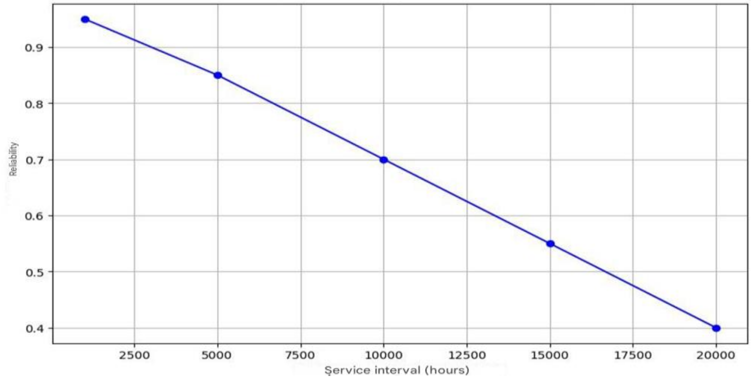

Figure 4. Impact of maintenance frequency on the reliability of SPP

Considering that vibration and thermal loads significantly accelerate degradation (as demonstrated in Table 5), the main engine and cooling system are particularly critical. For these components, it is advisable to adopt a shortened maintenance cycle after 10,000 hours of operation.

Economic assessment of maintenance strategies

Given the identified relationships between reliability and operational factors, the next step is to evaluate how preventive actions impact not only technical performance but also the overall lifecycle costs of SPP equipment. To assess the economic efficiency of different maintenance strategies, a comparative cost analysis was conducted for two operational scenarios: reactive maintenance (repair after failure only); scheduled preventive maintenance (every 5,000 hours). The main engine was selected as the case study component, being the most cost-critical in terms of failure consequences and downtime losses. The economic evaluation model is structured as follows:

$$C = C_{PM}(\Delta) + C_{rep} + C_{down}[R(t)],$$

where $C_{PM}(\Delta)$ - denotes the cost of preventive maintenance at interval Δ;

C_{rep} - direct costs of failure recovery;

C_{down} - losses associated with equipment downtime, which depend on the failure probability *R(t)* and the duration of recovery operations

In the reactive maintenance scenario, the number of failures over 25,000 hours of operation averaged 12, with total costs (repair + downtime) reaching 26.2 thousand USD. In contrast, with regular maintenance performed at 5,000-hour intervals, the number of failures was reduced to 4, and the total expenses amounted to 5.3 thousand USD. Table 7 presents a summary of the economic comparison between the two approaches. To formally compare these scenarios using key economic metrics, Table 7 below provides a comparison of failure frequency, repair costs, downtime-related losses, and total expenditures.

Table 7

Comparative assessment of main engine maintenance costs under different strategies (25,000-hour cycle)

Operation scenario	Number of failures over 25,000 h	Repair costs C_{rep}, thousand USD	Downtime losses C_{down}, thousand USD	Total costs C, thousand USD
Without regular maintenance	12	5.8	20.4 (≈12 h downtime)	26.2
With regular maintenance (every 5,000 h)	4	1.9	3.4 (≈2 h maintenance downtime)	5.3

As shown in the table, the scheduled maintenance strategy reduces the total number of failures by a factor of three and the overall costs by more than 4.5 times. At the same time, the equipment reliability at the end of the evaluated operational interval remains above 90%, which is confirmed by the results of simulation modeling using the reliability function R(t). The graph (Fig. 4) also demonstrates that extending the maintenance interval to 20,000 hours leads to a decrease in the probability of failure-free operation to 40%.

Thus, the economic evaluation confirms the practical effectiveness of implementing preventive maintenance. The recommended interval of 5,000 hours ensures an optimal balance between operational expenditures and the reduction of failure risks. The proposed approach is scalable to other subsystems of the SPPs and can be integrated into digital twins for dynamic optimization of maintenance strategies in real time.

4 Discussion of results

The conducted study demonstrates the effectiveness of an integrative approach to reliability assessment and the development of maintenance strategies for SPP equipment. Unlike classical methods based on stationary assumptions (e.g., the exponential model with constant failure rates), the proposed methodology combines analytical degradation models, non-stationary Markov processes, and discrete-event simulation modeling. This combination enables accounting for both damage accumulation and the influence of variable operational conditions, including vibration, temperature, and load regime.

Comparison with contemporary research confirms the relevance and scientific soundness of the proposed approach. For instance, several studies (Mauro & Kana [22]; Lv & Lv [23]) consider digital twins as a promising architecture for predictive control of maritime equipment. However, the authors emphasize the need for model unification and the integration of physically interpretable parameters. The present study meets these requirements: the reliability models are formalized, and the degradation parameters are directly dependent on operational impacts. In the works of Minchev et al. [24], digital twins are used for diagnostics and condition monitoring of marine diesel units, but the aspect of economic feasibility of maintenance is not addressed. In contrast, this study presents an evaluation of total costs under different maintenance strategies, thereby enhancing the practical significance of the results. The economic analysis conducted showed that switching from a reactive to a scheduled strategy (with a 5,000-hour interval) reduces total expenses by more than 4.5 times while increasing equipment reliability by 18–22%. The reliability optimization methods proposed by Zhou et al. [25] are based on particle swarm algorithms and are aimed at individual technological processes (e.g., cylinder block machining), without considering degradation dynamics during operation. In this study, the parametric degradation model with four technical condition states allows adaptation to changing conditions, reflecting the actual behavior of equipment over a long operational interval. The review by Liang et al. [26] highlights the lack of quantitative models capable of accounting for operational impacts such as overheating and vibration. This limitation is overcome in the present work: the developed reliability models incorporate temperature, load, and vibration parameters as arguments of the failure rate function. The introduced threshold values (e.g., 110 °C for oil, 120 °C for windings) are consistent with simulation results and may serve as the basis for automatically generating warning signals in digital twins. The work by D'Agostino et al. (2020) [27] is devoted to multiphysical modeling of ship microgrids in real time, but it lacks a reliability analysis component. The present study can be integrated into such systems, complementing them with residual life assessment and maintenance schedule optimization modules.

One of the key results of the study is the quantitative comparison of four reliability forecasting models. The simulation model demonstrated the highest accuracy (RMSE = 0.05), which is 33% better than that of the Markov model (0.08), and 58% better compared to the exponential model (0.12). The integrated metric Ψ, combining RMSE, AIC, BIC, and χ^2 with expert weights, confirmed the superiority of the hybrid model, demonstrating that accounting for the temporal dynamics of operational factors and degradation processes significantly improves the accuracy of long-term forecasting. Moreover, the study revealed differentiated sensitivity of various SPP components to operational loads. The most vulnerable components were the main engine and cooling system, for which increases in vibration and temperature lead to a sharp decline in reliability. In particular, by 20,000 hours, reliability decreases to 0.52 for the main engine and 0.48 for the cooling system. The generator and ship power station exhibit more stable behavior ($R \approx 0.60$ and 0.58, respectively), confirming the rationale for a differentiated approach to maintenance scheduling.

The practical value of the presented models lies in their ability to support informed managerial decisions regarding equipment maintenance and lifecycle management. Mathematical interpretability, integration capability within digital twins, and consistency with operational parameters make the proposed methodology promising for implementation in ship technical monitoring and decision support systems.

At the same time, the study has certain limitations. First, the input data used are averaged operational profiles that do not include streaming telemetry. Second, the model parameters were identified based on historical data and are not updated in real time. These limitations define directions for future research, including the incorporation of sensor streams, implementation of online calibration, expansion of the component base, and the use of machine learning methods for adaptive model tuning and adjustment of the integrated criterion Ψ.

Thus, the proposed integrative approach to modeling the reliability and maintenance of SPP equipment represents a balanced solution that combines mathematical rigor, engineering applicability, and economic efficiency. It may serve as a foundation for the development of intelligent prognostic systems within the framework of digitalization of marine vessel technical operations.

5 Conclusions

This study has achieved its stated objective: an integrated approach to long-term reliability analysis of SPP components has been proposed and substantiated. The approach combines physically interpretable failure rate dependencies, a non-stationary Markov framework, and simulation modeling of operational scenarios, while also linking the results to the economic efficiency of maintenance strategies.

The developed models enabled a quantitative assessment of the reliability of four key SPP subsystems over a 25,000-hour horizon. According to the simulation results, the probability of failure-free operation by the end of the cycle was approximately 30% for the main engine, 45% for the generator, 35% for the cooling system, and 42% for the ship power station. These figures highlight the need for overhaul or replacement of the most vulnerable components after 20,000 hours of operation. The root mean square error (RMSE) of failure prediction, when compared with field statistics, was 0.05 for the simulation model, 0.08 for the Markov model, and 0.12 for the exponential model—demonstrating a 33% improvement in accuracy over the nearest alternative and a 58% improvement over the baseline constant failure rate model. The integrated criterion Ψ, combining RMSE, AIC, BIC, and χ^2 with weights of 0.4:0.3:0.2:0.1, confirmed the superiority of the hybrid simulation–Markov scheme across all components.

The analysis of operational factors revealed that a 20% increase in relative load accelerates the growth of failure intensity by up to 1.7 times, and cooling water temperatures above 85 °C reduce the remaining life of the cooling system by 30%. The optimal preventive maintenance interval, determined using the residual risk function and economic criterion, was found to be 5,000 hours. With this periodicity, the total costs (maintenance + repairs + downtime) over a 25,000-hour cycle do not exceed 5.3 thousand USD, whereas foregoing scheduled maintenance increases costs to 26.2 thousand USD more than 4.5 times higher.

The practical value of this work lies in the ability to integrate the developed mathematical module into prognostic systems of SPP digital twins, enabling shipowners to recalculate, in real time, the failure probability, remaining life, and financial consequences of a chosen maintenance strategy. Future research prospects include online calibration of model parameters based on streaming data from ship technical monitoring and control systems, expansion of the component base of the digital twin, and the use of machine learning methods for automatic tuning of weights in the Ψ criterion.

References

1. Вычужанин, В. В. (2009). Повышение эффективности эксплуатации судовой системы комфортного кондиционирования воздуха при переменных нагрузках (Монография). Одесса: ОНМУ.

2. Вычужанин, В. В. (2012). Информационное обеспечение мониторинга и диагностирования технического состояния судовых энергоустановок. Вісник Одеського національного морського університету. Збірник наукових праць, (35), 111–124.

3. Вычужанин, В. В., & Рудниченко, Н. Д. (2019). Методы информационных технологий в диагностике состояния сложных технических систем: Монография. Одесса: Экология.

4. Vychuzhanin, V., & Vychuzhanin, A. (2025). 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. https://doi.org/10.36059/978-966-397-516-0

5. Vychuzhanin, V. V., & Rudnichenko, N. D. (2019). *Metody informatsionnykh tekhnologiy v diagnostike sostoyaniya slozhnykh tekhnicheskikh sistem: Monografiya*. Odessa: Ekologiya.

6. Zocco, F., Wang, H.-C., & Van, M. (2023). Digital twins for marine operations: A brief review on their implementation. *arXiv:2301.09574*. https://doi.org/10.48550/arXiv.2301.09574

7. Stadtmann, F., Wassertheurer, H. G., & Rasheed, A. (2023). Demonstration of a standalone, descriptive, and predictive digital twin of a floating offshore wind turbine. *Ocean Renewable Energy*. https://doi.org/10.1115/OMAE2023-103112

8. Polverino, L., Abbate, R., Manco, P., Perfetto, D., Caputo, F., Macchiaroli, R., & Caterino, M. (2023). Machine learning for prognostics and health management of industrial mechanical systems and equipment: A systematic literature review. *International Journal of Engineering Business Management, 15.* https://doi.org/10.1177/18479790231186848

9. Kaklis, D., Varlamis, I., Giannakopoulos, G., Varelas, T. J., & Spyropoulos, C. D. (2023). Enabling digital twins in the maritime sector through the

lens of AI and Industry 4.0. *International Journal of Information Management Data Insights, 3*(2). https://doi.org/10.1016/j.jjimei.2023.100178

10. Nezhada, M. M., Neshat, M., Sylaios, G., & Garcia, D. A. (2024). Marine energy digitalization: Digital twin's approaches. *Renewable and Sustainable Energy Reviews, 191,* 114065. https://doi.org/10.1016/j.rser.2023.114065

11. Mavrakos, A. S., Tsaousis, T., Faggioni, N., Caviglia, A., & Manzo, E. (2024). A digital twin approach for selection and deployment of decarbonization solutions for the maritime sector. In *State-of-the-Art Digital Twin Applications for Shipping Sector Decarbonization*. https://doi.org/10.4018/978-1-6684-9848-4.ch002

12. Liang, Q., Knutsen, K. E., Vanem, E., Æsøy, V., & Zhang, H. (2024). A review of maritime equipment prognostics health management from a classification society perspective. *Ocean Engineering, 301,* 117619. https://doi.org/10.1016/j.oceaneng.2024.117619

13. Han, P., Ellefsen, A. L., Li, G., & Holmeset, F. T. (2021). Fault detection with LSTM-based variational autoencoder for maritime components. *IEEE Sensors Journal, 21*(19). https://doi.org/10.1109/JSEN.2021.3105226

14. Xiao, B., Zhong, J., Bao, X., Chen, L., Bao, J., & Zheng, Y. (2024). Digital twin-driven prognostics and health management for industrial assets. *Scientific Reports, 14,* 13443. https://doi.org/10.1038/s41598-024-63990-0

15. Cui, Y., Sun, Y., Cui, J., Zhao, F., & Yuan, M. (2025). Digital twin for marine diesel engine: Enhancing predictive maintenance and operational efficiency. In *CSAA/IET International Conference on Aircraft Utility Systems (AUS 2024).* ResearchGate. https://www.researchgate.net/publication/388039483

16. Birolini, A. (2017). *Reliability engineering* (8th ed.). Springer. https://doi.org/10.1017/aer.2019.87

17. Tobias, P. A., & Trindade, D. C. (2011). *Applied reliability* (3rd ed.). Chapman and Hall/CRC. https://doi.org/10.1201/b11787

18. International Organization for Standardization. (2013). *ISO 12110-2:2013 Metallic materials — Fatigue testing — Variable amplitude fatigue testing — Part 2: Cycle counting and related data reduction methods.* https://cdn.standards.iteh.ai/samples/54713/496f47ac9d9e40b7af2c43f0bad42aff/ISO-12110-2-2013.pdf

19. Rausand, M., & Hoyland, A. (2004). *System reliability theory: Models, statistical methods, and applications* (2nd ed.). John Wiley & Sons. https://content.e-bookshelf.de/media/reading/L-571449-baa4bae2ce.pdf

20. Rubinstein, R. Y., & Kroese, D. P. (2017). *Simulation and the Monte Carlo method* (3rd ed.). Wiley. https://doi.org/10.1002/9781118631980

21. Burnham, K. P., & Anderson, D. R. (2002). *Model selection and inference: A practical information-theoretic approach* (2nd ed.). Springer-Verlag. http://dx.doi.org/10.1007/b97636

22. Mauro, F., & Kana, A. A. (2023). Digital twin for ship life cycle: A critical systematic review. *Ocean Engineering, 269,* 113479. https://doi.org/10.1016/j.oceaneng.2022.113479

23. Lv, Z., Lv, H., & Fridenfalk, M. (2023). Digital twins in the marine industry. *Electronics, 12,* 2025. https://doi.org/10.3390/electronics12092025

24. Minchev, D., Vasilev, K., & Petkov, P. (2023). Digital twin test bench performance for marine diesel engine applications. *Polish Maritime Research, 30*(4), 81–91. https://doi.org/10.2478/pomr-2023-0061

25. Zhou, H., Yang, W., Sun, L., Jing, X., & Li, G. (2021). Reliability optimization of marine diesel engine block machining using improved PSO method. *Scientific Reports, 11,* 21983. https://doi.org/10.1038/s41598-021-01567-x

26. Liang, Q., Knutsen, K. E., Vanem, E., Æsøy, V., & Zhang, H. (2024). A review of maritime equipment health prognostics from a classification society perspective. *Ocean Engineering, 301,* 117619. https://doi.org/10.1016/j.oceaneng.2024.117619

27. D'Agostino, F., Kaza, D., Martelli, M., Schiapparelli, G. P., Silvestro, F., & Soldano, C. (2020). Development of a multiphysics real-time simulator for model-based design of a DC shipboard microgrid. *Energies, 13*(10), 3580. https://doi.org/10.3390/en13143580

ІНТЕГРОВАНЕ МОДЕЛЮВАННЯ НАДІЙНОСТІ ТА ТЕХНІЧНОГО ОБСЛУГОВУВАННЯ ОБЛАДНАННЯ СУДНОВОЇ ЕНЕРГЕТИЧНОЇ УСТАНОВКИ З УРАХУВАННЯМ ЗНОШЕННЯ ТА ЕКСПЛУАТА

Dr.Sci. В. Вичужанін[1[0000-0002-6302-1832]]**, Ph.D. А. Вичужанін**[2[0000-0001-8779-2503]]
Національний університет «Одеська політехніка» Україна
EMAIL: [1]v.v.vychuzhanin@op.edu.ua, [2]vychuzhanin.o.v@op.edu.ua

Анотація. *Підвищення надійності та економічної ефективності морських суден вимагає розробки інструментів прогнозування відмов, здатних враховувати реальні умови експлуатації та процеси деградації обладнання. У статті представлено інтегрований підхід до кількісної оцінки надійності ключових компонентів енергетичної установки судна (ЕУС) на інтервалі експлуатації 25 000 годин. Методологія поєднує ймовірнісні, деградаційні та імітаційні моделі з урахуванням експлуатаційних параметрів, таких як температура, відносне навантаження та інтервали технічного обслуговування. Розроблено та порівняно чотири класи моделей відмов: експоненціальну модель, модель зі змінною інтенсивністю (нестаціонарний процес Вейбулла), чотиристанову марковську схему та імітаційну модель на основі подійного Монте-Карло. Розрахунки виконано для головного двигуна, генератора, системи охолодження та суднової електростанції. Середньоквадратична похибка (RMSE) прогнозу відмов становила 0,05 для імітаційної моделі, 0,08 для марковської моделі та 0,12 для експоненціальної моделі. Інтегрований критерій якості моделі, що враховує RMSE, AIC, BIC та*

χ^2, підтвердив перевагу гібридного імітаційно-марковського підходу. Порівняльний економічний аналіз показав, що регулярне технічне обслуговування з інтервалом 5000 годин знижує загальні витрати більш ніж у 4,5 раза порівняно з реактивними стратегіями ремонту. Практична цінність методу полягає в можливості його застосування у цифрових двійниках та інтелектуальних системах підтримки прийняття рішень. Подальші розробки передбачають розширення компонентної бази моделі, інтеграцію з потоками даних у реальному часі із суднових систем моніторингу та застосування методів машинного навчання для автоматичного налаштування параметрів.

Ключові слова: *предиктивна діагностика; цифровий двійник; залишковий ресурс; інтервально-орієнтоване обслуговування; марковська модель; імітаційне прогнозування; економічна оцінка відмов.*

УДК 004.896:519.8:614.8
DOI https://doi.org/10.36059/978-966-397-538-2-19

РОЗРОБКА ІНФОРМАЦІЙНОЇ ТЕХНОЛОГІЇ ДЛЯ БАГАТОКРИТЕРІАЛЬНОГО АНАЛІЗУ НЕСТІЙКОСТІ АВТОЗАПРАВНИХ СТАНЦІЙ ДО ТИПОВИХ АВАРІЙНИХ ПОДІЙ

Ph.D. О. Іванов[1][0000-0002-8620-974X], **Ph.D. D. Jones**[2][0000-0002-9101-746X],
Dr.Sci. О. Арсірій[1][0000-0001-8130-9613], **Ph.D. A. Labib**[3][0000-0002-5481-5833],
Ph.D. С. Смик[1][0000-0001-7020-1826]

[1]Національний університет «Одеська політехніка», Україна,
[2]Lion Gate Building, University of Portsmouth, Portsmouth, United Kingdom,
[3]Faculty of Business and Law, University of Portsmouth, Portsmouth, United Kingdom
EMAIL: lesha.ivanoff@gmail.com, dylan.jones@port.ac.uk, e.arsiriy@gmail.com, ashraf.labib@port.ac.uk, smyk@op.edu.ua

Анотація. *Це дослідження присвячене проєктуванню та впровадженню інтелектуальної інформаційної технології (ІТ), спрямованої на багатофакторне оцінювання нестійкості автозаправних станцій (АЗС) до типових небезпечних подій. Пропонована інтелектуальна ІТ структурована у 10 дискретних послідовних етапів. Початкові етапи процесу розробки включали точне визначення домінантних типів загроз, релевантних для АЗС, та ґрунтовний аналіз нестійкості АЗС, розглянутий крізь призму потенційних негативних наслідків. З цією метою експертами в предметній області було ретельно встановлено 41 метрику (критерій). Для уточнення цього набору даних застосовується метод аналізу ієрархій для аналізу експертних думок, що дозволяє вивести редукований критеріальний простір нестійкості з виключенням метрик, пов'язаних із летальними випадками. На основі цього*