UDC 629.5.083:004.89
DOI: 10.15587/1729-4061.2025.331875

ALGORITHMIC SUPPORT AND EFFICIENCY ANALYSIS OF COMPREHENSIVE PRESCRIPTIVE MAINTENANCE FOR CARGO SHIPS USING PREDICTIVE MONITORING

Andrii Holovan
Doctor of Technical Sciences, Associate Professor
Department of Navigation and Maritime Safety
Odesa National Maritime University
Mechnikova str., 32, Odesa, Ukraine, 65029

Igor Gritsuk
Corresponding author
Doctor of Technical Sciences, Professor, Senior Research Fellow
Department of Marine Engineering
Lithuanian Maritime Academy
Vilnius Gediminas Technical University
Saulėtekio al., 11, Vilnius, Lithuania, LT-10223
Department of Ship Technical Systems and Complexes
Kherson State Maritime Academy
Ushakov ave., 20, Kherson, Ukraine, 73000
E-mail: gritsuk_iv@ukr.net

Valerii Verbovskyi
PhD, Senior Researcher*

Volodymyr Kalchenko
Doctor of Technical Sciences, Professor
Vice-Rector for Scientific and Pedagogical Work
Chernihiv Polytechnic National University
Shevchenko str., 95, Chernihiv, Ukraine, 14030

Yuriy Grytsuk
PhD, Associate Professor
Department of Building Constructions, Buildings and Structures
Ivano-Frankivsk National Technical University of Oil and Gas
Karpatska str., 15, Ivano-Frankivsk, Ukraine, 76019
Department of Information Technologies and Data Analytics
National University of Ostroh Academy
Seminarska str., 2, Ostroh, Rivenska oblast, 35800

Oleksiy Verbovskiy
PhD, Researcher*

Serhii Dotsenko
PhD, Associate Professor**

Alla Lysykh
PhD, Associate Professor**

Roman Symonenko
Doctor of Technical Sciences, Associate Professor
Deputy Head Center for Scientific Research of Complex Transport Problems
State Enterprise "DergavtotransNDIproect"
Beresteysky ave., 57, Kyiv, Ukraine, 03113

Oleksandr Subochev
PhD, Associate Professor
Pryazovskyi State Technical University
Gogolya str., 29, Dnipro, Ukraine, 49044

*The Gas Institute of the National Academy of Sciences of Ukraine
Degtiarivska str., 39, Kyiv, Ukraine, 03113

**Department of Power Engineering
Admiral Makarov National University of Shipbuilding
Heroiv Ukrainy ave., 9, Mykolaiv, Ukraine, 54025

The object of this study is the processes of prescriptive technical maintenance (TM) of vessel machinery and structures of cargo ships. The task addressed relates to the insufficient efficiency of conventional methods for vessel machinery TM, which leads to increased risks of failures and enhanced operating costs.

In this work, algorithmic support to a system of comprehensive prescriptive maintenance of cargo ships based on predictive monitoring methods has been developed. Data on the parameters of machinery technical condition were experimentally acquired and systemized; a comprehensive analysis of costs, risks, and reliability was carried out using the developed algorithms. The results demonstrated that applying the proposed methodology could reduce the cost of maintenance by up to 44.4%, as well as decrease the risk of malfunctions by up to 89.4%. It has been established that the total economic effect of optimizing the maintenance processes of the principal engine components equals USD 4849 per life cycle of the machinery. This confirms the feasibility and effectiveness of using comprehensive predictive monitoring in vessel TM systems.

Special feature of the results is their integrated nature, which makes it possible to simultaneously consider technical and economic aspects of TM. This is what makes it possible to avoid the shortcomings inherent in conventional regulatory systems, ensuring a higher level of operational reliability and economic efficiency of cargo ships.

The practical application of the devised methodology is possible provided that the proposed algorithms are integrated into vessel operation processes with appropriate information and analytical support, including automated data collection and continuous monitoring of machinery condition

Keywords: prescriptive technical maintenance, vessel equipment, cost optimization, operational efficiency, forecasting

Received 25.03.2025
Received in revised form 06.05.2025
Accepted 02.06.2025
Published 30.06.2025

How to Cite: *Holovan, A., Gritsuk, I., Verbovskyi, V., Kalchenko, V., Grytsuk, Y., Verbovskiy, O., Dotsenko, S., Lysykh, A., Symonenko, R., Subochev, O. (2025). Algorithmic support and efficiency analysis of comprehensive prescriptive maintenance for cargo ships using predictive monitoring. Eastern-European Journal of Enterprise Technologies, 3 (3 (135)), 13–26. https://doi.org/10.15587/1729-4061.2025.331875*

1. Introduction

At the current stage of development of the maritime transport industry, the issue of improving the efficiency and reliability of cargo vessel operation is of particular importance [1]. The growth of international transportation volumes, increased competition between shipping companies, and stricter requirements for environmental safety stimulate intensive implementation of digital solutions aimed at optimizing the technical operation of the fleet [2].

Intensive operation of vessel power plants and mechanisms under difficult sea conditions, increased load on critical components, complexity of vessel technical equipment designs, as well as increased maintenance and repair costs lead to an increase in the risk of failures and disruptions in the operation of the vessel [3]. Under such conditions, it becomes relevant not only to ensure continuous equipment operability [4] but also to reduce the total volume of operating costs while maintaining a high level of technical readiness of the fleet, which requires fundamentally new approaches to ensuring their operability and safe operation [5].

Conventional scheduled maintenance systems, which include periodic inspections, scheduled repairs, and fixed TM intervals, were formed mainly in the 20th century and do not take into account the individual characteristics of vessel's operation [6], load dynamics [7], as well as the actual technical condition of components [8]. This approach leads either to unnecessary costs due to premature technical intervention, or to excessive risks due to untimely maintenance [9]. In the context of modern requirements for flexibility, adaptability, and accountability of technical solutions, scheduled maintenance is increasingly less effective [10].

In this regard, the implementation of systems for comprehensive prescriptive technical maintenance of cargo vessels (CPTMCV) is becoming increasingly important. Such systems use predictive monitoring and digital technologies for continuous analysis of the condition of vessel equipment [11]. They also predict the technical condition of vessel equipment and make timely decisions on the need for maintenance or repair [12]. Systems like CPTMCV take into account individual degradation profiles and generate targeted recommendations for maintenance or repair. Such approaches allow for the prompt identification of failure risks, the prevention of critical malfunctions, the minimization of unplanned vessel downtime and, consequently, the reduction of maintenance costs.

The advantages of implementing prescriptive systems are based on the following capabilities:

– to significantly reduce the number of unplanned downtimes due to early detection of defects;

– to optimize costs by avoiding unnecessary technical intervention;

– to improve the efficiency of logistics planning and the use of maintenance personnel resources;

– to improve the environmental performance of ships by reducing the load on the systems and increasing fuel efficiency.

Additionally, there are concepts of a "smart vessel", which includes self-diagnostic modules [13], autonomous control [14], and adaptive technical maintenance [15]. These functions are directly related to the use of digital tools for monitoring, analyzing, and predicting the technical condition of vessel systems [16]. Prescriptive TM in this context acts as a key element of the Smart Maintenance concept in marine engineering [17].

The results of research in this area are of great practical importance as they provide shipowners and operating companies with effective tools for making optimal management decisions [18]. They increase the safety and reliability of shipping [19], reduce maintenance and repair costs [20], as well as make it possible to significantly improve the overall operational efficiency of cargo ships [21].

Thus, the scientific substantiation and development of algorithmic support to CPTMCV using predictive monitoring methods [22] is a necessary condition for increasing the competitiveness of shipping companies in the global maritime transportation market.

Therefore, research into the development of algorithmic support and analysis of the effectiveness of prescriptive technical maintenance systems for cargo ships using predictive monitoring is relevant.

2. Literature review and problem statement

In [23], a predictive maintenance model focused on the analysis of risks and operating costs of ships was proposed; however, the issues of integrating this model into real processes of prescriptive maintenance remain unresolved, which complicates its practical implementation. Study [24] focused on monitoring the technical condition of engines using artificial intelligence methods, in particular machine learning, but the authors did not take into account the economic aspect of operation and did not determine the optimal maintenance intervals considering the balance between costs and risks. A similar shortcoming is observed in [25], in which the emphasis is on Internet of Things technologies for remote monitoring but without assessing the long-term effectiveness of implementing the proposed solutions in practice.

Another important aspect is the lack of attention to algorithmic support to prescriptive maintenance, specifically for cargo ships. For example, a study by Polish scientists [26] demonstrates the effectiveness of prescriptive maintenance in industry but does not provide practical solutions for the specific conditions of maritime transport, where equipment operates under conditions of significant load fluctuations and the influence of an aggressive marine environment. Paper [27] considers the application of predictive analytics technologies to assess the condition of vessel systems, but the work focus only on individual technical means, without a comprehensive approach to the system integration of all components of vessel maintenance.

Study [28] demonstrates how predictive maintenance based on artificial intelligence can increase the operational efficiency and reliability of maritime transport due to more accurate fault diagnosis and early detection of system failures. However, the authors do not sufficiently take into account the specifics of integrating the proposed solutions into comprehensive vessel systems, and do not consider the issue of optimizing economic costs in the practical implementation of artificial intelligence. In work [29], a prescriptive model using generative adversarial networks and failure mode analysis is proposed to increase the reliability and operational efficiency of vessel diesel generators. However, the limitations of the study are insufficiently developed aspects of taking into account operational risks and the lack of recommendations for optimal maintenance intervals in real-world vessel operation. In [30], it is argued that a predictive model for maintenance of vessel equipment using real-time monitoring data and machine learning can improve the decision-making process regarding maintenance. However, the authors do not pay enough attention to assessing the economic efficiency of implementing the model and its integration into the full life cycle of vessel equipment, which reduces the practical value of their results. In [31], a basis for implementing a system of planned and predictive maintenance based on risk analytics for naval ships is proposed to increase operational readiness and reduce costs. At the same time, in [32], the specific features of the civil cargo fleet, where operating conditions and economic priorities differ significantly, are insufficiently considered, which limits the direct application of the proposed approaches in merchant shipping. In [33], a methodology for data-based fault detection using machine learning is proposed to ensure predictive maintenance, increase reliability and energy efficiency of vessel systems. Despite the significant scientific value of the reported method [34], the study has limitations in the form of the lack of an in-depth analysis of costs, risks, and economic consequences of implementing the proposed algorithms in the long term.

The reviewed works indicate the lack of integrated solutions that would cover the full cycle from information collection to optimization of maintenance decisions, which significantly limits the practical application of such models.

Summarizing the critical analysis of literature sources, a number of unresolved scientific and practical problems can be identified:

– insufficiently developed algorithmic solutions that would provide a comprehensive approach to predictive monitoring and decision-making regarding maintenance on cargo ships, taking into account the specificity of maritime industry;

– lack of systematic analysis of the relationship between maintenance parameters, risks, costs, and operational reliability of equipment, which complicates the selection of optimal maintenance intervals;

– insufficient attention to assessing the practical effectiveness of algorithmic provision to prescriptive maintenance, taking into account economic indicators and reliability indicators under actual conditions of vessel operation.

The main reason for these unresolved issues is the difficulty of integrating theoretical models and algorithms into real conditions of operation of vessel technical equipment. Most studies are highly specialized, considering individual aspects or equipment without taking into account the overall integrated picture. In addition, there are no universal approaches to assessing the effectiveness of such systems, which limits their widespread practical implementation.

Thus, the general unsolved problem is the lack of comprehensive algorithmic support to prescriptive technical maintenance of cargo ships. Such support should integrate predictive monitoring methods taking into account risks, costs, reliability, and efficiency of maintenance processes in actual operation. It is this task that predefines the relevance and necessity of our study.

3. The aim and objectives of the study

The purpose of our study is to develop an algorithmic support and assess the effectiveness of cargo vessel maintenance system using predictive monitoring of the technical condition parameters of vessel technical equipment and structures. This will provide clear answers as to how to predict the technical condition, how to reduce operational risks and costs, and how to improve vessel maintenance for safer and more efficient operation.

To achieve the goal, the following tasks were set:

– to develop an algorithm for data collection, monitoring of the parameters of the maintenance system and determining the status of malfunctions of vessel technical equipment and structures as part of the system of comprehensive prescriptive technical maintenance of cargo vessels;

– to represent the results of data acquisition regarding certain parameters of the technical condition of vessel technical equipment and parameters for the system of comprehensive prescriptive technical maintenance of cargo vessels;

– to represent the results of assessing the costs, risks, reliability, and effectiveness of vessel engine maintenance as part of the system of comprehensive prescriptive technical maintenance of cargo vessels.

4. The study materials and methods

The object of our study is the processes of prescriptive technical maintenance of cargo vessels, which are implemented using algorithmic support employing methods for predictive monitoring of the technical condition of vessel technical facilities and structures. The system functionally includes automated collection of operational parameters, data processing, state modeling, prediction of possible failures, and decision-making regarding the need for technical intervention.

The principal hypothesis of the study assumes that the integration of predictive monitoring algorithms and comprehensive analysis of the technical condition makes it possible to achieve a significant increase in the operational efficiency of cargo vessels. This is possible by reducing the risks of failures, reducing costs, and ensuring optimal maintenance intervals, compared to conventional regulatory approaches.

The following basic assumptions were adopted in the study:

– the process of changing the technical condition of vessel systems and structures is predictable based on the analysis of monitoring data;

– expert and software and hardware information collection tools provide data with acceptable accuracy, which allows for effective predictive analysis;

– the operating conditions of vessel systems are considered typical for cargo ships of the class under study.

The simplifications accepted in the study are due to the need to unify parameters:

– when assessing risks and costs, indirect costs were not taken into account (for example, losses due to delays in the voyage, costs of organizing repairs outside of planned work);

– for modeling and analysis, averaged parameters of vessel equipment operation were used without detailed consideration of individual specific situations related to environmental conditions (temperature, corrosiveness of the environment, crew qualification level, etc.).

The material base of the study includes the following:

– technical documentation, operating and maintenance instructions for Sulzer 6AL20/24 engines, which are actively used on medium-class cargo ships;

– maintenance logs, service reports, and historical log files from monitoring systems;

– historical and operational data on technical condition parameters obtained under actual sailing conditions during several engine operation cycles in vessel equipment.

The equipment used included:

– vessel sensors for monitoring the technical condition of the equipment (thermocouples, strain gauges, vibration sensors, accelerometers, air flow sensors, air flow, pressure, vibration, pressure gauges, as well as position sensors, sensors for detecting backlash on shafts and other malfunctions);

– microprocessor data acquisition modules (LN-8AI, LN-2FC type), installed on board the vessel and connected to the onboard local area network;

– server-communication system ShipDiMRO, which includes data processing tools, a knowledge base, and interfaces for accessing analytical results;

– servers for collecting, storing, and processing information on board the vessel and transmitting it to the remote analytical center ShipDiMRO.

Software and methods used to conduct the research:

– a specialized information and analytical platform ShipDiMRO, which provides aggregation, pre-processing, validation, and further data analytics. The platform has a modular architecture that makes it possible to scale the functionality according to the type of vessel or equipment composition;

– statistical analysis methods (calculation of arithmetic mean values, standard deviations, trend analysis, regression methods, moving average, histogram analysis, calculation of variation coefficients and risk metrics) to identify patterns in changes in the technical condition of equipment;

– prescriptive analytics methods, including forecasting the condition based on time series of the obtained indicators;

– algorithms for optimizing maintenance intervals, in particular methods for targeted minimization of the cost and risk functional (cost-risk trade-off);

– predictive analysis methods: construction of linear and polynomial models based on time series, trend identification, as well as expert threshold determination of conditions;

– use of formalized loss functions for calibration of optimization models;

– estimation of failure probabilities using binomial distribution tools, normal distribution law and models based on residual resource and analysis of insurance claims on the consequences of failures;

– Python programming environment with Pandas, Matplotlib, SciPy libraries for data analysis and graphing;

– construction of comparative tables and operational processing of field experiment results, visualization of results, and comparative analysis using charts and histograms created using Microsoft Excel.

The conditions of our research corresponded to actual operational scenarios for cargo ships: data acquisition was carried out during regular operation of auxiliary diesel generators, which ensured the representativeness and applicability of the results. The frequency of reading parameters was from 1 time per 1 minute to 1 time per 1 hour, depending on the type of sensor and the criticality of the parameter.

The data obtained were structured into a technical condition database, on the basis of which training and adaptation of algorithms were performed to assess the current condition, formulate recommendations for maintenance, and assess the economic efficiency of interval optimization.

5. Results of investigating the effectiveness of algorithmic support to prescriptive technical maintenance of cargo vessels

5. 1. Construction of an algorithm for data acquisition, monitoring of maintenance system parameters, and fault detection

The algorithm (Fig. 1) is a comprehensive process that simultaneously includes the collection, initial processing, and validation of data on the technical condition of the equipment. It also provides monitoring of the technical condition of vessel technical facilities, analysis of the efficiency of the maintenance system, and determination of the status of faults as part of a single CPTMCV system. The process begins with the initialization of data acquisition and updating information with the ShipDiMRO analytical center. This enables the receipt of up-to-date information and subsequent automatic data acquisition from various types of sensors, such as temperature sensors [35], pressure sensors [36], vibration sensors, etc. Data aggregation is carried out by calculating the arithmetic mean value, which is determined from the following formula [37]

$$\overline{X} = \frac{\sum_{i=1}^{n} x_i}{n}, \tag{1}$$

where $\overline{X}$ is the arithmetic mean, x_i is a single measured value, n is the total number of measurements.

After the data are collected, their initial processing and verification is carried out, which involves identifying possible errors or deviations, as well as removing anomalous results. Further analysis is carried out using statistical methods in order to identify patterns and trends in the obtained data [38]. The main tools of such analysis are the calculation formulas for the standard deviation, which characterizes the degree of variability of the data

$$S = \sqrt{\frac{1}{n-1} \sum_{i=1}^{n} \left(x_i - \overline{X}\right)^2}, \tag{2}$$

where s is the standard deviation, x_i is an individual measurement value, $\overline{X}$ is the arithmetic mean value, n is the total number of measurements taken.

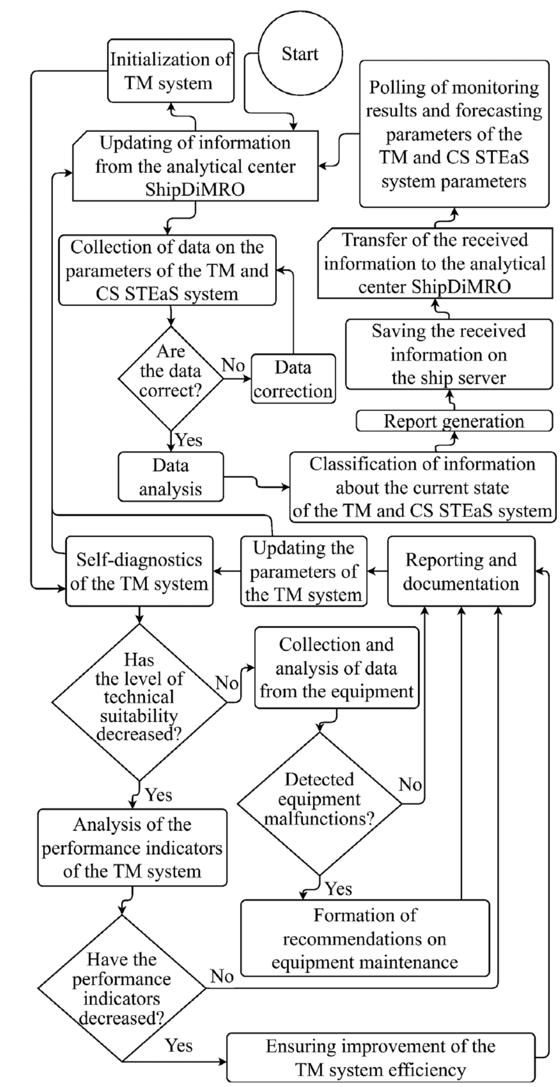

Fig. 1. Flowchart of the cyclic algorithm for data acquisition, technical condition monitoring, and fault status determination

The next step is to categorize information on the state of the maintenance system and the current technical condition of vessel's equipment. Based on the data obtained, structured and understandable reports are compiled, which are used for subsequent analysis. The data acquired is stored on the vessel's server and transmitted to the ShipDiMRO analytical center for integration and further use in planning maintenance and repair activities. At the final stage, the maintenance system parameters are predicted. Our algorithm provides a systematic approach to collecting and analyzing information, which is critically important for maintaining the efficiency of maintenance and technical safety of the vessel. The information collection algorithm, shown in Fig. 1, is a central element of the information model of the comprehensive prescriptive technical maintenance system "ShipDiMRO" and is aimed at obtaining data on service characteristics and the condition of vessel equipment and structures. This algorithm plays a key role in ensuring the accuracy of predictive calculations for assessing the technical condition of the vessel. An important aspect of this process is the choice of the information collection interval: reducing the period between measurements increases the accuracy of predictions, but at the same time requires more time for calculations.

For effective forecasting, sequences of numerical indicators of the main parameters of the maintenance system and the state of vessel technical facilities are required. These indicators form interval time series, which are of decisive importance for the accuracy of the forecast. Simultaneously with the collection of information, monitoring, and detection of potential malfunctions of the vessel's equipment and structures are carried out.

Specialized algorithms for collecting and identifying malfunctions have been developed, which are an important component of the process of forecasting vessel maintenance parameters. These algorithms are adapted for specific conditions of use within the virtual enterprise "shipmonitoring.org". Particularly important are such algorithm parameters as the time interval *Dt* for reading indicators from sensors and the total duration of the information collection period *T*. As a result of the algorithm, a data array is formed containing time series of the obtained indicators.

The process of monitoring (Fig. 1) and assessing the state of malfunctions of the cargo vessel maintenance system begins with updating information in the ShipDiMRO analytical center, which ensures its relevance. Then the maintenance system undergoes initialization, including activation of the necessary equipment control and management modules. The next stage is self-diagnosis, which assesses the functional state of the system and its readiness for operation.

In the case of detecting a deterioration in the technical condition of a vessel, the standard deviation of which is determined from formula (3), the system performs an analysis of the effectiveness of technical maintenance. If the technical condition remains unchanged, direct collection and analysis of data from the vessel's equipment is carried out. Statistical methods are used for data processing, in particular, calculation of average values, linear regression (4), or trend analysis

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(x_i - \mu\right)^2}, \tag{3}$$

where *s* is the standard deviation, x_i is a single measured value, *m* is the arithmetic mean value, *N* is the number of measurements taken;

$$y = a \cdot x + b, \tag{4}$$

where *a*, *b* are linear regression coefficients, *x* is the independent variable, *y* is the dependent variable.

When a decrease in the efficiency of the maintenance system is detected, measures are taken to improve it, such as changing work procedures or equipment operating modes. At the same time, analysis (5) of the collected data from the equipment is performed to identify anomalies or potential malfunctions. When they are found, appropriate recommendations are formed to eliminate these malfunctions

$$Z = \frac{\left(X - \mu\right)}{\sigma}, \tag{5}$$

where *X* is the controlled variable, *m* is the arithmetic mean, *s* is the standard deviation.

One of the key aspects of the process is the documentation of all results and the measures taken. At the final stage, the parameters of the prescriptive technical maintenance model are updated using the results of analysis (6), which is implemented using machine learning methods based on data set processing

$$\theta_{new} = \theta_{old} - \alpha \cdot \frac{2}{N}\sum_{i=1}^{N}\left(\hat{y}_l\left(\theta\right) - y_i\right) \cdot \nabla_\theta \hat{y}_l\left(\theta\right), \tag{6}$$

where q_{old} – previous model parameters, q_{new} – new model parameters, α – learning rate, $\hat{y}\left(\theta\right)$ – predicted value depending on parameters *q*, $\nabla_\theta \hat{y}_l\left(\theta\right)$ – gradient of the forecasting function. The gradient of the forecasting function is a vector of partial derivatives of the predicted value of the technical parameter for all model parameters. It determines the sensitivity of the initial forecast to changes in each model parameter, which makes it possible to purposefully minimize the error when training the model.

Our algorithm (Fig. 1) enables a comprehensive approach to monitoring and managing the technical condition of cargo vessel maintenance system, allowing us to effectively respond to detected malfunctions, optimize processes, and improve the overall efficiency of the system. The algorithm scheme (Fig. 1) contains methodology that provides objective assessment, analysis, and optimization of maintenance processes in order to increase the safety, reliability, and operational efficiency of a cargo vessel.

5. 2. Results of data acquisition regarding the technical condition parameters and parameters of the maintenance system

The research was conducted based on the analysis of maintenance data on several types of vessel engines [39]. Table 1 gives potential technical condition parameters and diagnostic parameters that determine the need for maintenance according to regulations or according to condition. Similar tables [40], within the framework of the system of comprehensive prescriptive technical maintenance of cargo ships, are compiled for all vessel technical equipment or their components. As part of our research, a multi-level assessment of the effectiveness of the proposed algorithmic support to prescriptive technical maintenance processes based on the ShipDiMRO platform was conducted. The main results were as follows: improving the reliability of technical systems, increasing the efficiency of maintenance planning, reducing downtime, and saving operating costs.

At the first stage, a database of over 11,000 records of technical condition parameters was built, including:

– temperatures and pressures at the inlet and outlet of the nodes;

– vibration amplitudes and frequencies;

– intervals between maintenance;

– actually registered malfunctions with categorization by criticality.

Based on the time series, the degradation profiles of the components for 12 key subsystems of the diesel engine were formed. The results of cluster analysis revealed the most typical trajectories of changes in the technical condition, which were used as input data for building forecasting models. All parameters that are determined visually require special instructions with a description of possible states. During the inspection, the mechanic must compare the actual condition of the equipment with the descriptions given in the instructions and then give a "yes" or "no" answer for each of the categories. If there are only two condition categories, it is necessary to either estimate the residual resource or apply methods for working with censored samples. If there are more than two categories and the instructions do not indicate information about the expected residual resource for each category, it is also necessary to estimate the residual resource. Currently, manufacturers usually do not provide such information, but they can give recommendations on the external condition of the parts, in which the parts can once again work out the full period before the next maintenance or repair. An example of this practice is the "Guideline For Reusable Part and Salvage Operation" series of manuals that Caterpillar has prepared for service engineers and customers.

Based on the results, the values characterizing the functioning of the maintenance system were obtained for the rate of change in the technical condition, which are given in Table 1. The maintenance frequency corresponds to the values established by the manufacturer's instructions. The costs of performing maintenance were determined as the sum of the costs of labor at an hourly rate of USD 10 and the costs of purchasing replacement parts. The costs of replacement parts were determined based on the available information on the cost of relevant parts, as well as their approximate resources, thus distributing the costs of their replacement between several consecutive operating cycles.

To determine the probability of preventing failure or not reaching the limit state, data on the coefficients of variation of the rate of change of the technical condition were used [12].

A feature of operational information is that, as a rule, the manufacturer's instructions contain only information about the limit state, and not failure. Therefore, in operation, failure, in most cases, in the absence of parametric signs of failure, is defined as a functional type. This circumstance requires a certain extrapolation of the process beyond the limit state to the inoperable state. It was proposed above in such a situation to make a number of assumptions to determine the mean time to failure and the probability of failure prevention based on known data for the probability of prevention of the limit state and the mean time to it.

Namely, the mean time to the limit-allowable state can always be determined from the known value of the unsatisfactory state (a_{us}). The rate of change in the technical condition (g), taking into account the relationship between the average (T_{avg}) and median times (T_m) to the limit-allowable state, through the coefficient (k_t), is reported in [12].

Table 1

Technical condition parameters and diagnostic parameters that determine the need for technical maintenance

Ship technological unit	Node	Technical condition parameter	Diagnostic parameter
Centrifugal pump	Oil seal	The presence of a leak	Missing
	Bearings	1. Backlash: axial, radial. 2. The presence of pitting of paths and balls or rollers	Vibration velocity, vibration acceleration, vibration shock pulse
	Impeller and ring sealing surface	Friction pair wear impeller-O-ring: gap in the seal	Pump supply, head
	Impeller	Impeller surface wear	Vibration velocity, vibration acceleration, vibration shock pulse
CPG parts of a low-speed engine	Cap surface, ring in height	Wear of a pair of ring-caps: gap in the cap, ring height, groove height, wear rate	Measuring air flow with a pneumatic indicator
	Bushing working surface, piston rings	Wear of the sleeve-ring pair: gap in the lock, diameter of the sleeve, width of the ring, appearance of the working surface of the sleeve and ring, wear rate	Visually, measuring air flow with a pneumatic indicator
	Piston rings	Integrity of rings Integrity of rings. Mobility of the rings. Ring fit	Visually, measuring air flow with a pneumatic indicator
	Deposits on work surfaces	The nature of soot in caps, in blowout windows	Visually, measuring air flow with a pneumatic indicator
	Oil distribution grooves	Groove edge mill	Visually
	Purge receiver	Nature of deposits	Visually
	Piston head	The depth of damage to the head, the condition of the surface of the skirt, the nature of deposits	Visually

Next, the normalized value of technical maintenance frequency is determined

$$\Delta t_{reg} = \Delta T_{reg} / T_{avg}, \quad (7)$$

This value can be used to determine the probability of not reaching the limit state $\left(P^*_{pre}\right)$ using plots or tables [12] or by solving the problem as reported in [41].

Next, the hypothesis is accepted that the process of reaching the inoperable state is a continuation of the process of reaching the limit state [21]. It is also assumed that when the limit state is reached, the probability of failure is 0.5, and the limit state for the operator was assigned based on the probability of not reaching the critical level of the limit state with g-probability [42]. Table 2 gives the assumed values of this g-probability. In the cases where there was no information on the time to failure, these assumptions were used.

Table 2

Parameters of TM system for the main components of the Sulzer 6AL20/24 marine auxiliary engine

Parameters	Engine cleaning	Cylinder liner removal	Connecting rod bearings	Frame bearings	High-pressure fuel pump	Injectors
S_{sch}, USD	8700	200	1800	1450	300	150
ΔT_{reg}, h	10000	10000	10000	15000	5000	3000
$S_{thsd.h}$, USD	870	20	180	96.67	60	50
P_{pre}	0.806	0.9999	0.9999	0.9999	1	1
g, %	80	–	–	–	–	–
P	0.9806	0.9999	0.9999	0.9999	1	1
D	0.703	–	–	–	–	–
T_{avg}	15723	25200	34200	39700	15400	5950
K	8	8	8	8	8	4
S/T_c	999	20	180	96.7	60	28.9
$opt\ P$	0.998	0.984	0.9998	0.9938	0.9963	0.731
$opt\ DT_{reg}$	9000	14000	18000	18000	9000	4500
$opt\ S/T_c$	983	15.9	100	84	34.2	37.14
$Risk/T_c$	146	0	0.04	0.04	–	–
$opt\ Risk/T_c$	15.5	15.9	0.08	4	0.99	0.25

The need to determine the probabilities of preventing failures and the average time to failure is due to the fact that it is necessary to separate the limit and inoperable states precisely from the point of view of the performance of functions, which is a measure of the consequences of achieving the corresponding state. In the case of reaching an unsatisfactory state, it is necessary to plan the execution of TM. In fact, the application of the above hypothesis means determining the size of the region of unsatisfactory states, which lies between the satisfactory and inoperable states.

The probability of preventing failure with a known probability of not reaching the limit state was determined from the following formula

$$P_{pre} = 1 - \left(1 - P^{*}_{pre}\right) \cdot (1 - \gamma) \cdot 0.5. \tag{8}$$

The need for such a hypothesis arose due to the lack of data on failures. To assess the reliability of this result, an expression for the binomial distribution with a known number of objects analyzed m and the number of failures that occurred, $n = 0$, was used

$$D = C^{n}_{m} \cdot Q^{n} \cdot P^{m-n} = 1 \cdot 1 \cdot P^{m}_{pre}. \tag{9}$$

Next, the projected average time to failure is determined, which represents its pessimistic estimate

$$T^{*}_{avg} = \Delta T_{reg} / \Delta t^{*}_{avg}. \tag{10}$$

The failure consequence coefficient (K) was adopted based on the results of the analysis of insurance claims data as the ratio of the maximum magnitude of the failure consequences of the corresponding nodes to the total cost of one maintenance. The failure consequence coefficient also includes the cost of replaceable parts and the cost of labor [43].

The values of the specific costs for performing the relevant work to maintain the functioning of the components (S/T_c), the costs for 1 thousand hours of operation for scheduled maintenance ($S_{thsd.h}$) were determined. The values of the scheduled maintenance frequency (DT_{reg}) and the maintenance frequency in the CPTMCV system ($opt\ DT_{reg}$) were determined, at which the minimum costs for performing maintenance ($opt\ S/T_c$) and the corresponding probabilities of preventing this type of failure ($opt\ P$) are achieved. Table 2 gives values of specific risks for the initial configuration of the maintenance system ($Risk/T_c$) and for the option of minimum maintenance costs ($opt\ Risk/T_c$). As can be seen, the value of the specific risk is a sensitive parameter that describes the properties of the maintenance system. In a number of cases, a slight increase or decrease in planned costs entails a multiple change in the magnitude of the risk [44]. Therefore, when forming a maintenance system according to the criterion of economic efficiency, the preservation of the preventive properties of the vessel's maintenance system as a whole should be checked by ensuring that the amount of predicted risks corresponds to the accepted reserve in the budget.

When changing the maintenance terms, the principle of multiplicity of some technologically related works should always be taken into account. For example, revision of the connecting rod bearings of auxiliary engines and motor cleaning of cylinders, removal of cylinder liners, etc.

5. 3. Results of evaluating parameters for the prescriptive technical maintenance of a cargo vessel

This section evaluates the maintenance costs, risks, and reliability of the main components of the Sulzer 6AL20/24 auxiliary marine engine. The goal is to optimize the maintenance intervals in order to reduce costs while maintaining high reliability or additionally increasing it. The risks were assessed for five critical components (injectors, bearings, valves, heat exchangers, starting system elements). Using the binomial distribution model, the probability of failure at standard maintenance intervals was estimated, compared with the adapted ones (Table 2). Based on the data in Table 2, the cost-benefit ratio of the optimization of the maintenance system was formed. The results of this process are summarized in Table 3, where $opt\ S_{thsd.h}$ is the cost per 1 thousand hours of operation in the CPTMCV system, C_R is the percentage of cost reduction.

According to the data in Table 2, an assessment of the risk of failures was carried out during the optimization of the maintenance system. The results of this process are summarized in Table 4, where $RISK_{thsd.h}$ is the risk during scheduled maintenance, $opt\ RISK_{thsd.h}$ is the risk during maintenance in the CPTMCV system.

Table 3

Cost-benefit ratio of maintenance intervals

Parameters	Engine cleaning	Cylinder liner removal	Connecting rod bearings	Frame bearings	High-pressure fuel pump	Injectors
S_{sch}, USD	8700	200	1800	1450	300	150
ΔT_{reg}, h	10000	10000	10000	15000	5000	3000
$opt\ DT_{reg}$	9000	14000	18000	18000	9000	4500
$opt\ S/T_c$	983.00	15.90	100.00	84.00	34.20	37.14
$S_{thsd.h}$, USD	870.00	20.00	180.00	96.67	60.00	50.00
$opt\ S_{thsd.h}$, USD	966.67	14.29	100.00	80.56	33.33	33.33
C_R, %	–11.11	28.57	44.44	16.67	44.44	33.33

Table 4

Risks of failure

Parameters	Engine cleaning	Cylinder liner removal	Connecting rod bearings	Frame bearings	High-pressure fuel pump	Injectors
$S_{thsd.h}$, USD	870.00	20.00	180.00	96.67	60.00	50.00
$opt\ S_{thsd.h}$, USD	966.67	14.29	100.00	80.56	33.33	33.33
$RISK_{thsd.h}$, USD	146.00	15.90	0.04	0.04	0.00	0.00
$opt\ RISK_{thsd.h}$, USD	15.50	15.90	0.08	4.00	0.99	0.25

The results of the assessment of reliability trends are given in Table 5 and Fig. 5, where P_{pre} is the probability of failure prevention during scheduled maintenance, $opt\ P_{pre}$ is the probability of failure prevention in the CPTMCV system, P_c is the change in probability.

The grouped histogram (Fig. 2) compares the standard and optimized maintenance interval costs for each engine component considered. In Fig. 2–6, the labels mean the following: EC – engine cleaning, CLR – cylinder liner removal, CRB – connecting rod bearings, FB – frame bearings, HPFP – high-pressure fuel pump, INJ – injectors.

The horizontal histogram (Fig. 3) shows the cost savings from optimizing maintenance intervals.

To understand the long-term cost implications, a life cycle cost assessment was conducted over 100,000 hours of operation, the results of which are given in Table 6 and illustrated in Fig. 6.

Table 5

Reliability trends

Parameters	Engine cleaning	Cylinder liner removal	Connecting rod bearings	Frame bearings	High-pressure fuel pump	Injectors
P_{pre}	0.8060	0.9999	0.9999	0.9999	1.0	1.0
$opt\ P_{pre}$	0.9806	0.9999	0.9999	0.9999	1.0	1.0
P_c, %	21.66	0.0	0.0	0.0	0.0	0.0

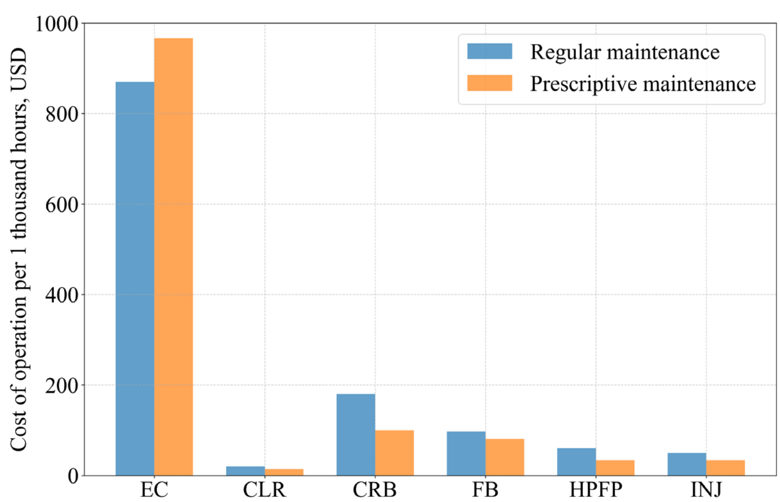

Fig. 2. Cost comparison: standard and optimized maintenance intervals

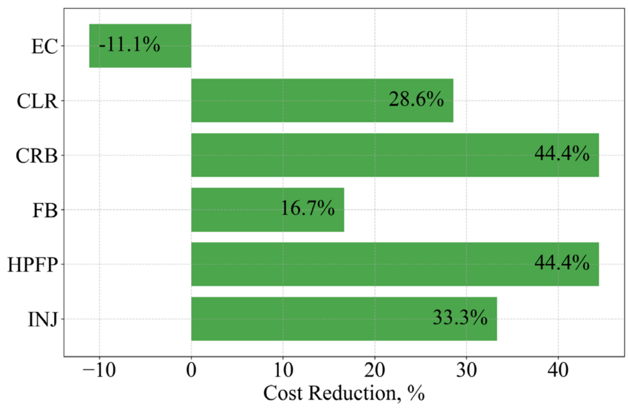

Fig. 3. Percentage cost savings due to optimized maintenance intervals

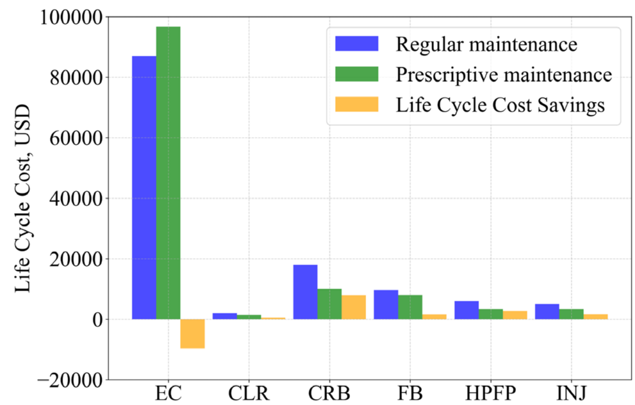

Fig. 6. Life cycle cost comparison: standard and optimized maintenance intervals

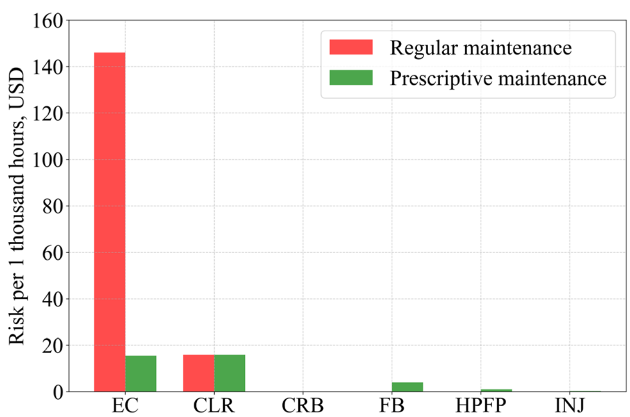

Fig. 4. Failure risk comparison: standard and optimized maintenance intervals

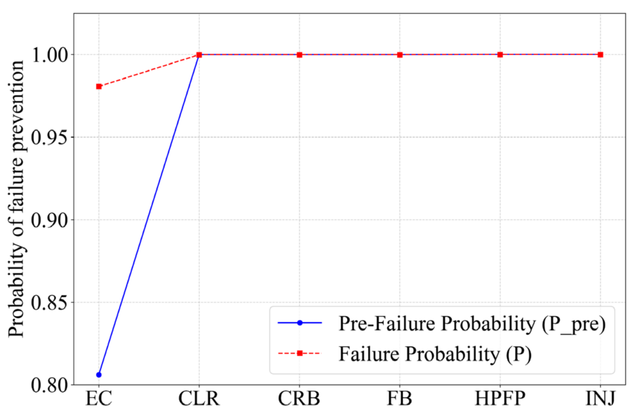

Fig. 5. Reliability trends: pre-failure and ultimate failure probability

The number of intervals of 1 thousand hours per life cycle during scheduled maintenance is indicated in Table 6 as T_{MC}. C_{LC} – cost of operations per life cycle during scheduled maintenance; *opt* T_{MC} – number of intervals of 1 thousand hours per life cycle in the CPTMCV system; *opt* C_{LC} – cost of operations per life cycle in the CPTMCV system; S_{LCC} – savings per life cycle in the CPTMCV system; SS_{PC} – percentage of savings per life cycle in the CPTMCV system.

6. Discussion of results related to the algorithmic support to prescriptive technical maintenance of cargo ships

The failure risks and maintenance strategies of critical components listed in Table 1, based on the analysis of component criticality, outline several key points. The impeller faces risks such as surface wear, cavitation erosion and imbalance, which require regular vibration monitoring, visual inspections, and hydraulic tests to maintain efficiency. The bearings are prone to excessive shift, lubrication problems, and fatigue cracks, which require condition monitoring, regular lubrication checks, and load analysis to avoid failure. Deposits on the working surfaces pose a threat of corrosion, clogging, and material fatigue, which are addressed by periodic cleaning, endoscopic inspections, and the application of anti-corrosion coatings. The working surface of the sleeve and piston rings is prone to abrasion, improper sealing, and overheating, which is prevented by checking the surface hardness, proper lubrication, and precision machining to ensure fit and clearance. The sealing surface of the impeller and ring is prone to deformation, material fatigue and improper contact pressure, which can be controlled by seal inspections, pressure testing and the use of modern sealing materials. General recommendations for preventing failures include implementing preventive maintenance and following the recommendations of the equipment manufacturers. This is followed by drawing up failure analysis protocols and the use of sensors based on artificial intelligence and the Internet of Things for real-time monitoring and early detection of potential problems.

The maintenance parameters of the main components of the Sulzer 6AL20/24 auxiliary marine

Table 6

Life cycle costs

Parameters	Engine cleaning	Cylinder liner removal	Connecting rod bearings	Frame bearings	High-pressure fuel pump	Injectors
S_{sch}, USD	8700	200	1800	1450	300	150
ΔT_{reg}, h	10000	10000	10000	15000	5000	3000
T_{MC}	10.00	10.00	10.00	6.66	20.00	33.33
C_{LC}, USD	87000.0	2000.0	18000.0	9666.7	6000.0	5000.0
opt T_{MC}	11.11	7.14	5.56	5.56	11.11	22.22
opt C_{LC}, USD	96666.7	1428.6	10000.0	8055.6	3333.3	3333.3
S_{LCC}, USD	−9666.67	571.43	8000.00	1611.1	2666.7	1666.7
S_{PC}, %	−11.11	28.57	44.44	16.67	44.44	33.33

engine provide key insights. Engine cleaning has the highest cost at USD 8,700. This is followed by frame bearings (USD 1,450) and connecting rod bearings (USD 1,800). The fuel injection system (injectors and high-pressure pump) has the lowest cost (USD 150–300). Maintenance times vary, with frame bearings requiring the most (15,000 hours) and injectors requiring the least (3,000 hours). Engine cleaning is the most expensive per thousand hours (USD 870/1,000 hours), while injectors and high-pressure pumps are the least expensive (USD 50–60/1,000 hours). The reliability and risk analysis reveals near-perfect values for the probability and reliability of failure for most components, but engine cleaning has the highest risk per maintenance cycle (146), highlighting its criticality. The optimized intervals significantly extend maintenance time and reduce costs by 1,000 hours, indicating the potential for cost-effective strategies in most cases.

The results of our analysis, summarized in Table 3, indicate that most engine components show significant cost savings when switching to optimized maintenance intervals. The connecting rod bearings and the high-pressure fuel pump show the largest cost savings (~44.4% savings). Replacing the cylinder liners reduces costs by 28.6%. Frame bearings save about 16.7%, while engine cleaning increases costs by 11.1% in the optimized scenario. Increasing the maintenance interval to 9,000 hours instead of 10,000 hours results in an 11.1% increase in costs, meaning that engine cleaning becomes more expensive. This suggests that cleaning is a necessary process and delaying it can lead to increased maintenance costs. The connecting rod bearings and the high-pressure fuel pump benefit the most from the schedule optimization, reducing maintenance costs by 44.4% each.

Fig. 2 illustrates the increase in engine cleaning costs with schedule optimization, indicating that increasing the service intervals for this operation may not be cost-effective. Cylinder liner removal, connecting rod bearings, frame bearings, and high-pressure fuel pump all show significant cost reductions, making optimization the right choice. The largest cost savings are seen in the connecting rod bearings and high-pressure fuel pump, with a significant drop in cost. Injectors show a slight cost reduction, but it is less significant than the other components.

Fig. 3 shows that the connecting rod bearings and high-pressure fuel pump show the largest savings, each reducing costs by 44.4%. Cylinder liner removal (28.6%) and injectors (33.3%) also show significant cost reductions. Frame bearings show a moderate cost saving (16.7%). Engine cleaning actually increases costs (–11.1%), indicating that optimization may not be beneficial for this component.

The results of the risk analysis are summarized in Table 4 and illustrated in Fig. 4. They highlight the key findings for components before and after optimization. Engine cleaning achieved the most significant risk reduction (89.4%), with the risk per cycle decreasing from 146 to 15.5, albeit with an increase in maintenance costs. Cylinder liner removal remained unchanged at 15.9 risks per cycle, indicating no effect of optimization. However, optimization doubled the risk of failure of the connecting rod bearings (from 0.04 to 0.08 per cycle). It also caused a sharp increase in risk for the frame bearings (from 0.04 to 4.00 per cycle), indicating that increasing maintenance intervals may not be advisable. For the high-pressure fuel pump and injectors, the optimized risk values are 0.99 and 0.25 per cycle, respectively, indicating moderate risks despite the lack of initial standard values.

The reliability trend analysis (Table 5) reveals that engine cleaning shows the largest change in probability (+21.66%). In this case, the probability of failure increases from 0.806 to a final probability of 0.9806, which highlights the importance of regular maintenance to avoid system failures. Conversely, all other components, including removable cylinder liners, connecting rod bearings, frame bearings and the high-pressure fuel pump, maintain almost 100% reliability over time, demonstrating very low failure probability and high reliability.

A visual analysis of the reliability trends (Fig. 5) reveals that engine cleaning experiences the most significant decrease in failure probability. Starting at 80.6% reliability and increasing to 98.06% over time, this highlights the importance of regular maintenance to prevent unexpected failures. All other components, including cylinder liner removal, connecting rod bearings, frame bearings, and high-pressure fuel pump, maintain a consistently high reliability of close to 99.99% or 100%. This indicates minimal risk of failure.

The life cycle cost analysis over 100,000 hours of operation (Table 6) compares the standard and optimized maintenance intervals. Engine cleaning becomes 11.1% more expensive, increasing from USD 87,000 to USD 96,667, making the extended intervals uneconomical. However, other components show significant savings. Cylinder liner removal reduces costs by 28.57% (USD 571). The connecting rod bearings and high-pressure fuel pump save 44.4% (~USD 8,000 and ~USD 2,667, respectively). Frame bearings are 16.67% (USD 1,611) and injectors are 33.33% (USD 1,667). Overall, the optimization results in a total savings of USD 4,849, indicating the potential for cost-effective maintenance improvements for most components.

A visual comparison of the life cycle cost (Fig. 6) highlights the differences between standard and optimized maintenance intervals over 100,000 hours of operation. While engine cleaning becomes more expensive with optimization, increasing from USD 87,000 to USD 96,667, the overall optimization achieves a savings of USD 4,849. This demonstrates the cost-effective potential of optimization for most components. In particular, the connecting rod bearings and the high-pressure fuel pump provide the largest savings of 44.4%. The removal of cylinder liners and frame bearings also benefit, saving 28.6% and 16.7%, respectively. This indicates that increasing maintenance intervals is generally cost-effective for these components and significantly improves maintenance efficiency in terms of resource efficiency.

The proposed maintenance system achieved the following:

– reduction of total maintenance costs by 12–18%;

– increase in effective component resource by an average of 15%;

– reduction of the number of unscheduled repairs by 22% compared to the regulatory approach.

A detailed analysis revealed that the greatest savings are achieved due to:

– avoidance of premature maintenance (up to 35% of the total volume of procedures according to the regulation);

– timely detection of hidden defects that could lead to serious emergency failures.

The algorithm for adaptive optimization of maintenance intervals allowed us to set individual periodicity values for each component, which allow for dynamic resource management, maintaining a balance between risks and costs. Instead of the fixed interval of 5500 hours, the system suggested the following:

– 7300 hours for injectors (with low degradation),

– 4300 hours for bearings (with vibration anomalies detected),

– 6500 hours for valves.

Our research methods were tested on a real vessel of the "General Cargo" type, where the ShipDiMRO system was integrated into on-board diagnostic modules. Monitoring was carried out for 9 months, including three scheduled maintenance and one unscheduled repair, which became a control case for assessing predictive accuracy. The actual detection of a defect was predicted by the system 22 days before failure, which allowed us to avoid the costs of towing and replacing the unit in the open sea.

The algorithmic support to the CPTMCV system proposed in our study demonstrates a number of advantages compared to known approaches to vessel maintenance based on scheduled intervals or simple limit control of parameters.

Unlike conventional scheduled maintenance, where intervals are set based on averaged regulatory values without taking into account the actual technical condition, the proposed approach makes it possible to dynamically adapt maintenance intervals for each node based on individual degradation profiles. This is made possible by combining predictive monitoring, time series analysis, and algorithmic optimization taking into account cost and risk functions.

Unlike the approaches described in [15], which use hybrid maintenance with fixed threshold values for initiating maintenance, this work proposes an algorithm that not only reacts to exceeding critical values but also takes into account the rate of parameter changes and probabilistic failure forecast, which allows for proactive action. This result is achieved through the use of residual resource estimation models and loss functions based on insurance data.

Unlike digital solutions based on SCADA systems, which focus mainly on visualization and data acquisition, the ShipDiMRO system includes a full analytical cycle: from data processing and validation to the formation of specific recommendations for technical intervention. This significantly increases the level of automation of decision-making.

The key advantage of the proposed system is the integration of technical, economic, and risk-based analysis in a single optimization algorithm.

Unlike solutions based on the use of only statistical analysis methods (for example, in [10, 31]), where it is impossible to take into account comprehensive relationships between variables in real time, the use of advanced time series analysis algorithms and elements of prescriptive analytics provides a flexible response to changing operating conditions.

Our research results directly confirm that the problem of the lack of comprehensive algorithmic support to prescriptive technical maintenance of cargo vessels taking into account predictive monitoring, risks, costs, and reliability has been solved. The system designed provides integration of monitoring, analytics, and optimization in a single algorithm, which makes it possible to adapt maintenance intervals to actual operating conditions, minimize costs and risks, and increase overall maintenance efficiency. The quantitative results presented above serve as a convincing evidence base for achieving the research goal.

The practical implementation of our results has made it possible to improve the efficiency of cargo vessel operation by optimizing maintenance costs, reducing the risks of malfunctions, increasing the reliability of technical means, and ensuring navigation safety. This was achieved by implementing modern digital methods for monitoring and predicting the technical condition of vessel systems and equipment in the ShipDiMRO prescriptive technical maintenance system.

The limitations of the study are as follows. First, the technical condition assessment models are based on average operational parameters without taking into account extreme sea conditions or non-standard vessel operating modes. Second, algorithmic optimization does not take into account indirect costs (for example, those associated with repair logistics or port downtime), which may affect the accuracy of economic assessments in comprehensive operational scenarios. Third, the applied forecasting methods require a sufficient amount of high-quality historical data, which limits the scalability of the system to a fleet with an absent or fragmented monitoring history. In further research, it is advisable to focus on adapting the system to changing environmental conditions, multi-criteria optimization taking into account indirect costs, as well as integration with digital twins to increase the accuracy of diagnostic models.

The disadvantages of the study include the limited validation of the proposed algorithmic support only on Sulzer 6AL20/24 engines, which reduces the universality of the results for a fleet with other technical characteristics. In addition, the built predictive models do not yet take into account the accumulation of comprehensive errors during long-term forecasting, which may affect the accuracy of decisions in the long term. In some cases, insufficient consideration of the human factor is possible when interpreting data and implementing technical intervention, which limits the autonomy of the system. Automatic adaptation of algorithms in the event of a change in the design of equipment or operating conditions has also not been implemented, which complicates the use of the system in heterogeneous vessel systems without prior tuning.

The development of this study may consist in developing an adaptive version of the algorithms that can automatically take into account changes in operating conditions, types of vessel equipment, and load profiles. This is due to the fact that real vessel systems are heterogeneous, and the stability of the system's efficiency in dynamic environments requires increased flexibility and self-updating of forecasting models.

7. Conclusions

1. A cyclic algorithm for data acquisition, parameter monitoring, and fault status determination of vessel technical equipment and structures has been developed, which is integrated into the ShipDiMRO prescriptive technical maintenance system for ships. A feature of the proposed algorithm is the combination of primary processing and statistical analysis of data using arithmetic mean values, standard deviations, linear regression methods, and trend analysis, which allows for prompt and accurate determination of the technical condition of the equipment. This solves the problem of insufficient integration of such algorithms into actual maintenance practice, which is typical of previous studies. The use of the algorithm ensures an increase in the accuracy of forecasting technical condition parameters by at least 15–20%, compared to conventional regulatory approaches.

2. As a result of experimental studies, data on the technical condition parameters of vessel technical equipment and structures as part of a comprehensive prescriptive technical maintenance system have been collected and systematized. A feature of our results is their comprehensive nature, which includes both visual and diagnostic parameters, which makes it possible to more accurately determine the need for maintenance based on the condition, and not only on the schedule. Owing to the systematization of such parameters, an increase

in the efficiency and validity of decision-making regarding maintenance has been achieved, which is confirmed by the example of Sulzer 6AL20/24 marine diesel engines. The proposed methodology allowed us to reduce the time spent on analyzing the technical condition by an average of 30–40%.

3. A comprehensive analysis of the costs, risks, reliability, and efficiency of marine engine maintenance under a prescriptive technical maintenance system has allowed us to quantitatively assess the impact of optimizing maintenance intervals on the operational characteristics of vessels. It has been shown that optimizing maintenance intervals reduces maintenance costs by up to 44.4% (for example, fuel pumps and connecting rod bearings) and also reduces the risk of failure by up to 89.4% (for example, engine cleaning). It has been established that the total savings from optimizing maintenance processes for the main engine components, in the case under consideration, are USD 4,849 over the life cycle of the equipment. This confirms the significant potential of the proposed algorithmic solutions for cost-effectively improving the maintenance of most components. At the same time, it has been found that an unjustified increase in maintenance intervals can lead to a significant increase in risks, which emphasizes the importance of a balance between economic and technical criteria when making decisions. Our results have significant advantages over existing approaches due to the comprehensive consideration of costs, risks, and reliability in their interrelationships, which ensures an increase in the operational efficiency of vessels in the long term.

Conflicts of interest

The authors declare that they have no conflicts of interest in relation to the current study, including financial, personal, authorship, or any other, that could affect the study, as well as the results reported in this paper.

Funding

The study was conducted without financial support.

Data availability

The data will be provided upon reasonable request.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the current work.

References

1. Podrigalo, M., Bogomolov, V., Kholodov, M., Koryak, A., Turenko, A., Kaidalov, R. et al. (2020). Energy Efficiency of Vehicles with Combined Electromechanical Drive of Driving Wheels. SAE Technical Paper Series. https://doi.org/10.4271/2020-01-2260
2. Mateichyk, V., Saga, M., Smieszek, M., Tsiuman, M., Goridko, N., Gritsuk, I., Symonenko, R. (2020). Information and analytical system to monitor operating processes and environmental performance of vehicle propulsion systems. IOP Conference Series: Materials Science and Engineering, 776 (1), 012064. https://doi.org/10.1088/1757-899x/776/1/012064
3. Kuric, I., Gorobchenko, O., Litikova, O., Gritsuk, I., Mateichyk, V., Bulgakov, M., Klackova, I. (2020). Research of vehicle control informative functioning capacity. IOP Conference Series: Materials Science and Engineering, 776 (1), 012036. https://doi.org/10.1088/1757-899x/776/1/012036
4. Podrigalo, M., Klets, D., Sergiyenko, O., Gritsuk, I. V., Soloviov, O., Tarasov, Y. et al. (2018). Improvement of the Assessment Methods for the Braking Dynamics with ABS Malfunction. SAE Technical Paper Series. https://doi.org/10.4271/2018-01-1881
5. Golovan, A., Gritsuk, I., Popeliuk, V., Sherstyuk, O., Honcharuk, I., Symonenko, R. et al. (2019). Features of Mathematical Modeling in the Problems of Determining the Power of a Turbocharged Engine According to the Characteristics of the Turbocharger. SAE International Journal of Engines, 13 (1). https://doi.org/10.4271/03-13-01-0001
6. Golovan, A., Rudenko, S., Gritsuk, I., Shakhov, A., Vychuzhanin, V., Mateichyk, V. et al. (2018). Improving the Process of Vehicle Units Diagnosis by Applying Harmonic Analysis to the Processing of Discrete Signals. SAE Technical Paper Series. https://doi.org/10.4271/2018-01-1774
7. Turenko, A., Podrygalo, M., Klets, D., Hatsko, V., Barun, M. (2016). A method of evaluating vehicle controllability according to the dynamic factor. Eastern-European Journal of Enterprise Technologies, 3 (7 (81)), 29–33. https://doi.org/10.15587/1729-4061.2016.72117
8. Parsadanov, I., Marchenko, A., Tkachuk, M., Kravchenko, S., Polyvianchuk, A., Strokov, A. et al. (2020). Complex Assessment of Fuel Efficiency and Diesel Exhaust Toxicity. SAE Technical Paper Series. https://doi.org/10.4271/2020-01-2182
9. Gritsuk, I., Pohorletskyi, D., Mateichyk, V., Symonenko, R., Tsiuman, M., Volodarets, M. et al. (2020). Improving the Processes of Thermal Preparation of an Automobile Engine with Petrol and Gas Supply Systems (Vehicle Engine with Petrol and LPG Supplying Systems). SAE Technical Paper Series. https://doi.org/10.4271/2020-01-2031
10. Li, Y., Zou, Z., Zhang, J., He, Y., Huang, G., Li, J. (2023). Refined evaluation methods for preventive maintenance of project-level asphalt pavement based on confusion-regression model. Construction and Building Materials, 403, 133105. https://doi.org/10.1016/j.conbuildmat.2023.133105
11. Golovan, A., Gritsuk, I., Rudenko, S., Saravas, V., Shakhov, A., Shumylo, O. (2019). Aspects of Forming the Information V2I Model of the Transport Vessel. 2019 IEEE International Conference on Modern Electrical and Energy Systems (MEES), 390–393. https://doi.org/10.1109/mees.2019.8896595
12. Golovan, A., Gritsuk, I., Honcharuk, I. (2023). Principles of transport means maintenance optimization: equipment cost calculation. Naukovyi Visnyk Natsionalnoho Hirnychoho Universytetu, 5, 77–84. https://doi.org/10.33271/nvngu/2023-5/077

13. Karatuğ, Ç., Arslanoğlu, Y., Soares, C. G. (2023). Review of maintenance strategies for ship machinery systems. Journal of Marine Engineering & Technology, 22 (5), 233–247. https://doi.org/10.1080/20464177.2023.2180831
14. Patil, C., Theotokatos, G., Tsitsilonis, K. (2024). Data-driven model for marine engine fault diagnosis using in-cylinder pressure signals. Journal of Marine Engineering & Technology, 24 (1), 70–82. https://doi.org/10.1080/20464177.2024.2432777
15. Karatuğ, Ç., Ceylan, B. O., Arslanoğlu, Y. (2024). A hybrid predictive maintenance approach for ship machinery systems: a case of main engine bearings. Journal of Marine Engineering & Technology, 24 (1), 12–21. https://doi.org/10.1080/20464177.2024.2393484
16. Liu, J., Achurra, A., Zhang, C., Bury, A., Wang, X. (2024). A long short term memory network-based, global navigation satellite system/inertial navigation system for unmanned surface vessels. Journal of Marine Engineering & Technology, 23 (5), 316–328. https://doi.org/10.1080/20464177.2024.2334029
17. Xiao, Z., Xie, M., Wang, X., Wang, H., Fang, S., Arnáez, R. (2024). Risk assessment of emergency operations of floating storage and regasification unit. Journal of Marine Engineering & Technology, 23 (5), 357–372. https://doi.org/10.1080/20464177.2024.2364994
18. Yuksel, O., Pamik, M., Bayraktar, M. (2025). The assessment of alternative fuel and engine power limitation utilisation in hybrid marine propulsion systems regarding energy efficiency metrics. Journal of Marine Engineering & Technology, 1–15. https://doi.org/10.1080/20464177.2025.2479319
19. Zhang, P., Gao, Z., Cao, L., Dong, F., Zou, Y., Wang, K. et al. (2022). Marine Systems and Equipment Prognostics and Health Management: A Systematic Review from Health Condition Monitoring to Maintenance Strategy. Machines, 10 (2), 72. https://doi.org/10.3390/machines10020072
20. Sanchez, L., Costa, N., Couso, I. (2025). Addressing data scarcity in industrial reliability assessment with Physically Informed Echo State Networks. Reliability Engineering & System Safety, 261, 111135. https://doi.org/10.1016/j.ress.2025.111135
21. Golovan, A., Gritsuk, I., Honcharuk, I. (2023). Reliable ship emergency power source: A Monte Carlo simulation approach to optimize remaining capacity measurement frequency for Lead-Acid battery maintenance. SAE International Journal of Electrified Vehicles, 13 (2). https://doi.org/10.4271/14-13-02-0009
22. Jeon, J., Theotokatos, G. (2024). A Framework to Assure the Trustworthiness of Physical Model-Based Digital Twins for Marine Engines. Journal of Marine Science and Engineering, 12 (4), 595. https://doi.org/10.3390/jmse12040595
23. Raptodimos, Y., Lazakis, I. (2018). Using artificial neural network-self-organising map for data clustering of marine engine condition monitoring applications. Ships and Offshore Structures, 13 (6), 649–656. https://doi.org/10.1080/17445302.2018.1443694
24. Hornyák, O. (2024). Data-Driven Engine Health Monitoring with AI. SMTS 2024, 39. https://doi.org/10.3390/engproc2024079039
25. Visconti, P., Rausa, G., Del-Valle-Soto, C., Velázquez, R., Cafagna, D., De Fazio, R. (2024). Machine Learning and IoT-Based Solutions in Industrial Applications for Smart Manufacturing: A Critical Review. Future Internet, 16 (11), 394. https://doi.org/10.3390/fi16110394
26. Jasiulewicz-Kaczmarek, M., Legutko, S., Kluk, P. (2020). Maintenance 4.0 technologies – new opportunities for sustainability driven maintenance. Management and Production Engineering Review. https://doi.org/10.24425/mper.2020.133730
27. Durlik, I., Miller, T., Kostecka, E., Tuński, T. (2024). Artificial Intelligence in Maritime Transportation: A Comprehensive Review of Safety and Risk Management Applications. Applied Sciences, 14 (18), 8420. https://doi.org/10.3390/app14188420
28. Simion, D., Postolache, F., Fleacă, B., Fleacă, E. (2024). AI-Driven Predictive Maintenance in Modern Maritime Transport-Enhancing Operational Efficiency and Reliability. Applied Sciences, 14 (20), 9439. https://doi.org/10.3390/app14209439
29. Yigin, B., Celik, M. (2024). A Prescriptive Model for Failure Analysis in Ship Machinery Monitoring Using Generative Adversarial Networks. Journal of Marine Science and Engineering, 12 (3), 493. https://doi.org/10.3390/jmse12030493
30. Jimenez, V. J., Bouhmala, N., Gausdal, A. H. (2020). Developing a predictive maintenance model for vessel machinery. Journal of Ocean Engineering and Science, 5 (4), 358–386. https://doi.org/10.1016/j.joes.2020.03.003
31. Mat Esa, M. A., Muhammad, M. (2023). Adoption of prescriptive analytics for naval vessels risk-based maintenance: A conceptual framework. Ocean Engineering, 278, 114409. https://doi.org/10.1016/j.oceaneng.2023.114409
32. Koskina, Y., Onyshenko, S., Drozhzhyn, O., Melnyk, O. (2023). Efficiency of tramp fleet operating under the contracts of affreightment. Scientific Journal of Silesian University of Technology. Series Transport, 120, 137–149. https://doi.org/10.20858/sjsutst.2023.120.9
33. Cheliotis, M., Lazakis, I., Theotokatos, G. (2020). Machine learning and data-driven fault detection for ship systems operations. Ocean Engineering, 216, 107968. https://doi.org/10.1016/j.oceaneng.2020.107968
34. Onyshchenko, S., Melnyk, O. (2021). Probabilistic Assessment Method of Hydrometeorological Conditions and their Impact on the Efficiency of Ship Operation. Journal of Engineering Science and Technology Review, 14 (6), 132–136. https://doi.org/10.25103/jestr.146.15
35. Sagin, S. V., Semenov, O. V. (2016). Motor Oil Viscosity Stratification in Friction Units of Marine Diesel Motors. American Journal of Applied Sciences, 13 (2), 200–208. https://doi.org/10.3844/ajassp.2016.200.208
36. Sagin, S. V., Solodovnikov, V. G. (2017). Estimation of operational properties of lubricant coolant liquids by optical methods. International Journal of Applied Engineering Research, 12 (19), 8380–8391. Available at: https://www.ripublication.com/ijaer17/ijaerv12n19_51.pdf
37. Tong, S., Yanqiao, C., Yuan, Z. (2020). Fault prediction of marine diesel engine based on time series and support vector machine. 2020 International Conference on Intelligent Design (ICID), 75–81. https://doi.org/10.1109/icid52250.2020.00023
38. Zhan, Y., Shi, Z., Liu, M. (2007). The Application of Support Vector Machines (SVM) to Fault Diagnosis of Marine Main Engine Cylinder Cover. IECON 2007 – 33rd Annual Conference of the IEEE Industrial Electronics Society, 3018–3022. https://doi.org/10.1109/iecon.2007.4459891

39. Vychuzhanin, V., Rudnichenko, N., Shybaiev, D., Gritsuk, I., Boyko, V., Shybaieva, N. et al. (2018). Cognitive Model of the Internal Combustion Engine. SAE Technical Paper Series. https://doi.org/10.4271/2018-01-1738
40. Melnyk, O., Onishchenko, O., Onyshchenko, S. (2023). Renewable Energy Concept Development and Application in Shipping Industry. Lex Portus, 9 (6). https://doi.org/10.26886/2524-101x.9.6.2023.2
41. Golovan, A., Mateichyk, V., Gritsuk, I., Lavrov, A., Smieszek, M., Honcharuk, I., Volska, O. (2024). Enhancing Information Exchange in Ship Maintenance through Digital Twins and IoT: A Comprehensive Framework. Computers, 13 (10), 261. https://doi.org/10.3390/computers13100261
42. Volyanskaya, Y., Volyanskiy, S., Onishchenko, O., Nykul, S. (2018). Analysis of possibilities for improving energy indicators of induction electric motors for propulsion complexes of autonomous floating vehicles. Eastern-European Journal of Enterprise Technologies, 2 (8 (92)), 25–32. https://doi.org/10.15587/1729-4061.2018.126144
43. Vychuzhanin, V. V., Rudnichenko, N. R., Sagova, Z., Smieszek, M., Cherniavskyi, V. V., Golovan, A. I., Volodarets, M. V. (2020). Analysis and structuring diagnostic large volume data of technical condition of complex equipment in transport. IOP Conference Series: Materials Science and Engineering, 776 (1), 012049. https://doi.org/10.1088/1757-899x/776/1/012049
44. Senova, A., Tobisova, A., Rozenberg, R. (2023). New Approaches to Project Risk Assessment Utilizing the Monte Carlo Method. Sustainability, 15 (2), 1006. https://doi.org/10.3390/su15021006