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ARTIFICIAL INTELLIGENCE TECHNIQUES FOR SHIP ELECTRICAL SYSTEM CONDITION MONITORING

The objective of this article is to analyze and organize AI techniques for predictive analytics of a vessel's technical state. The need comes from these types of technical equipment failures, representing over a quarter of all incidents at sea. The scientific novelty in this review is based on the lack of a comprehensive analysis of the best neural network architectures for predicting the failures of such critical nodes within the maritime industry, for example, including diesel generators and transformers. We consider how deep learning architectures evolved, with an increasing importance to consider how attention is being used to analyze complex time series, from simple Recurrent networks to state-of-the-art transformers. Specifically, we compare the Informer, PatchTST, and Autoformer models, emphasizing that the latter have a 38% enhancement in forecasting accuracy achieved by the addition of trend and seasonality decomposition blocks. The merits of neural network architectures (LSTMs) compared to classical statistical-based models (ARIMA) for modeling high-dimensional data in a precise maritime environment, such as maritime data, were highlighted. Finally, we introduce a new method of diesel engine fault detection based on SqueezeNet and IVY-RF algorithms. The Random Forest ensemble method has an accuracy for dissolved gas analysis (95.2%-100%) in transformer diagnostics. We further describe the employment of multi-task multilayer task networks MTL-DNN for electrical network protection against arcing and a method of analyzing circuit breaker fault contact wear without disassembly. The results are verified using testing. In summary, as a result of the present limitations, the future of marine predictive analytics is to create hybrid systems that will utilize the dynamic aspect that the machine learning method provides and the subject-matter knowledge that the user of the expert system has, in order to enhance safety and competitiveness in shipping.

Ke ywords: artificial intelligence, predictive analytics, Shipping 4.0, ship electrical equipment, fault diagnosis, technical condition monitoring, deep learning, neural networks.

Formulation of the problem. Over 80% of global cargo movements today are through shipping, and systems operating during shipping are essential for uninterrupted production. In 2024, as reported by EMSA [1], the breakdown of technical equipment accounts for 25.3% of all maritime accidents. Traditional maintenance methods – reactive and planned preventive – often fail, leading to expensive or variable blackouts as a result. Modern electrical equipment takes on many complexities, and certain stresses encountered in the marine environment (vibration, humidity, salt fog) result in the sudden requirement of automatic and predictive analysis to detect early-stage component degradation.

Analysis of recent research and publications. Recent research and publications are analyzed.

Marine predictive analytics research is littered with comprehensive reviews providing a systematic experience with the use of digital technologies. This chapter specifically suggests in [2] that the development of integrated monitoring systems is essential when considering predictive maintenance, yet it lacks unified approaches when considering the complex nature of ship power systems. The current debate of applying modern architectures when studying time series is described in detail in the review of large models [3], emphasizing the advantage of transformer architectures over recurrent networks in tasks of long-term forecasting, crucial for planning repair work planned on the voyage. While dedicated literature reviews [4] of marine internal combustion engines indicate

a trend to leverage machine learning methods for fault detection, they pointed to the dark box aspects of such deep neural networks as an important source of low interpretability. At the same time, research in the field of offshore energy [5] describes interesting wind turbine monitoring installations in wind turbine applications in combination with their implementation into hybrid ship systems. It is also worth mentioning that the work on AI-based techniques to localize damage in distribution networks through AI methods [6]. While there have been many publications, the majority of reviews have either not considered maritime-specific considerations or have only focused on general artificial intelligence algorithms, or have been specific to the ship nodes. The article seeks to contribute to bridging this gap with an extensive review of intelligent diagnostics technology for ship electrical systems.

Task statement. The purpose of this work is a comprehensive analysis and systematization of artificial intelligence methods for predictive analytics of the condition of ship electrical equipment. The study aims to review the most effective neural network architectures for predicting failures of critical components, such as diesel generators and transformers, and to justify the transition to integrated decision-making systems in the maritime industry.

Outline of the primary material of the study. Artificial intelligence is a large domain in computer science that centers its efforts around creating agents that allow them to perform tasks that were previously considered only as human intelligence. These include, for instance, learning, problem solving, perception, language understanding, and decision-making. The modern architecture of intelligent systems is built on a three-level hierarchy, where artificial intelligence serves as a fundamental concept to replicate human cognitive functions. The next level is represented by machine learning (ML), which refers to an algorithm's ability to identify latent patterns in data without explicit programming rules independently. The highest degree of specialization is provided by deep learning (DL), which, using multilayer artificial neural networks, implements mechanisms for detecting complex hierarchical patterns in large arrays of unstructured information [7]

Machine learning is the core of modern "statistical" AI. It differs fundamentally from "symbolic" AI (such as expert systems) in that rules of behavior are not programmed manually, but are derived (learned) directly from data. ML is divided into three main paradigms: supervised, unsupervised, and reinforcement learning. In supervised learning, a model uses labeled

data to perform classification (category prediction) and regression (numerical value prediction). In the case of unsupervised learning, the model uses unlabeled data to cluster things or to reduce their dimensionality (e.g., via PCA). Reinforcement learning involves an agent interacting by trial and error with the environment to maximize reward in control and optimization tasks. [7]

Deep learning is realized by implementing multilayer artificial neural networks (ANNs), the biggest benefit being the automated extraction of relevant features directly from the original datasets. This eliminates the subjectivity and laboriousness of manual feature engineering typical of classical machine learning. The modern typology of DL architectures includes convolutional networks (CNNs), which are deterministic and used for processing spatial grid structures in computer vision systems; recurrent networks (RNNs), which model complex time sequences; and generative adversarial networks (GANs), which focus on synthesizing high-fidelity data. [7]

The technological vanguard of the industry comprises third-generation neuromorphic networks (SNNs), which reproduce the dynamics of biological neurons, and hypernetworks, which, through the meta-learning paradigm, ensure high system adaptability and enable effective compression for operation on mobile devices. [8]

NLP is a branch of AI that enables machines to understand, interpret, analyze, and generate human language (text or speech). A large amount of management data consists of unstructured text (reports, emails, protocols, regulatory documents). Classic methods include syntactic and semantic analyses, such as bag-of-words. Modern techniques based on DL can be used for Sentiment Analysis – assessing the emotional coloring of the text (positive, negative, neutral); large language models (LLM – like ChatGPT) understand complex contexts, respond to queries, summarize meaningful texts, and generate new ones. [9]

Computer vision (CV) provides automated interpretation of visual information and has undergone a technological transformation enabled by deep learning algorithms. The functional spectrum of CV includes image classification for object identification; object detection, which involves simultaneous identification and localization; and semantic segmentation for pixel-by-pixel labeling of visual data, all of which are critical for autonomous navigation and obstacle recognition systems. [10]

Expert systems (ES) are a symbolic AI paradigm in which decisions are based on deterministic rules

rather than learning facts from statistical training. The ES framework consists of one part: a knowledge base (a collection of “if-then” heuristics), and the other part: a logical inference mechanism that runs off the input data. Autonomous agents (AA) serve as software or physical systems capable of interacting independently with the environment to implement goal functions. Alternatively, agent-based modeling reflects the dynamics of complex systems where a number of independent agents act together. [11]

The taxonomy described illustrates a fundamental shift in approaches. Classical systems analysis was well combined with symbolic AI and expert systems, since both required explicit, manual descriptions of rules and structures. However, for the study of complex “soft” management systems, where the rules are unknown or too complex, statistical AI (ML/DL) that learns these rules from data is an incomparably more powerful tool.

AI is most valuable when no single technology is used to analyze an incident, but only when multiple technologies and other systems are synergistically integrated within a single systems-analysis loop. For example, let’s review the complete automated incident analysis cycle:

1. NLP [9] automatically collects and structures operator reports, conversation recordings, and data from log files.
2. Data Mining Algorithms [11] analyze this structured data and find hidden correlations.
3. The ML model [7] builds a risk model from these patterns that predicts the probability of an incident occurring in real time.
4. The system automatically generates notifications and suggests specific corrective actions to the manager when the predicted risk exceeds the threshold.

Thus, AI enables the creation of an end-to-end, automated, and continuous system-analysis cycle that runs in parallel with the real management process.

The fundamental problem with traditional approaches, such as ARIMA (Autoregressive Integrated Moving Average), is that they suffer from the inability to learn the high-dimensional data and the time dependencies in ambiguous situations. In 2024, the studies clearly demonstrated the superiority of neural network-based approaches [12]. In particular, the efficiency of long short-term memory (LSTM) architectures in time-series forecasting tasks was assessed in comparison to the classical ARIMA model, with 85.1% accuracy, and ensemble methods like Random Forest (87.4%) at 89.3%. Moreover, LSTM scores much lower on errors (MAE=2.7,

RMSE=3.8), which makes these models absolutely indispensable when the total cost of errors is high.

In time series analysis, a combination of convolutional neural networks (CNNs) and long short-term memory networks has a synergistic effect. In this setup, the CNN's performance is efficient as a feature extractor for local patterns and invariant structures that have been extracted from raw input data (e.g., sensor spectrograms or multidimensional financial indicators). The resulting feature vectors are fed to LSTM layers that model time dependencies and long-range dynamics.

Most traditional approaches treat time series as a discrete data stream that does not account for the correlations between sources. Graph neural networks (GNNs) can solve this issue by learning the data as a graph and mapping it in such a way that the nodes represent entities (such as sensors, customers, warehouses) and the edges are interactions between them. Using heterogeneous GNNs has been successfully implemented for fraud detection in supply chain finance, which seeks to study complex transactional relationships between counterparties. GNNs allow for the collection of data from distributed sensors while maintaining network topology, and this is a very crucial issue because of the need for load prediction and energy saving optimization in industrial systems.

The Transformer architecture, originally made for natural language processing, has come a long way in the past few years for time series data, arguably the most. Transformers follow a self-attention mechanism; however, unlike RNNs (recurrent neural networks), which usually treat the same data in a sequential manner, they can experience vanishing gradients on long sequences. This makes it possible for the model to treat the relations among all time series' variables, at all distances, concurrently. [7] The development of transformer architecture has led to the creation of a series of specialized models, each with its own unique challenges for computational power and accuracy, as shown in Table 1.

The Autoformer model demonstrates an explicit decomposition and decomposes non-stationarity (the variation in the statistical properties of a series over time). This is a notable milestone in comparison with the “black boxes” of traditional transformers. [13]

Shipping 4.0 is a period of significant transformation of the shipping industry, responsible for more than 80% of the world's commercial cargo transport. This process has been characterized by the integration of computer-based systems in ships with IoT and artificial intelligence. The 2024 report from the United Nations Conference on Trade and Develop-

Transformer models architectures

Model	Architectural feature and mechanism	Advantages and scope of application	Limitations and challenges
Informer	Uses the ProbSparse mechanism Self-Attention, which selects only the most significant queries based on the KL-divergence metric, reducing the complexity from $O(n^2)$ to $O(n \cdot \log(n))$. [13]	Very efficient for ultra-long time series. That reduces memory requirements and greatly speeds inference.	In high-volatility data, sparse attention leads to loss of local detail.
Autoformer	It directly integrates the Decomposition Block into the architecture. It separates the series into trend and seasonality by using autocorrelation rather than conventional attention. [13]	Provides a 38% increase in long-term forecasting accuracy compared to analogues. Best for highly complex and non-stationary processes.	Greater architectural complexity complicates interpretations of the model's internal weights.
PatchTST	Time-series segmentation is implemented for patches (subseries patches) that are processed as discrete tokens, preserving semantic locality. [14]	The model helps in better capturing local patterns by adding fewer tokens, thus reducing computational cost.	Requires careful tuning of patch size and step hyperparameters.
Pyraformer	Implements a pyramidal attention graph for multiscale dependency and multiscale modeling. [14]	It captures dependencies with effective and linear complexity over short and long timescales.	There are fewer general libraries used for standard libraries, making it difficult to implement quickly.

ment (UNCTAD) states that last year, over 12 million cargo movements took place, and a steady year-on-year growth rate of 2.4% is estimated for the next 10 years up until 2029. This dynamic increase in shipping intensity imposes an increased burden on shipboard technologies, particularly electrical power systems, which play a vital role in guaranteeing the survival, navigation, and safety of the ship. Conventional maintenance methods, like reactive maintenance (maintenance after the accident) and planned preventive maintenance with predetermined intervals to maintain, are no longer very useful to the evermore intricate ship equipment. They frequently result in either too much maintenance of workable parts - and a raised production and maintenance cost - or a sudden emergency breakdown that endangers crew members and the cargo. [2] Accordingly, a shift to predictive maintenance with machine learning algorithms is more than just progress—it is also a prerequisite for keeping up with environmental standards and remaining competitive. Knowledge of failures (types and prevalence) is the cornerstone of building effective machine learning models. We need some deep historical analysis to solve these problems; otherwise, we will never be able to train an algorithm capable of learning patterns or failures that precede such things. The findings of system and apparatus failures are well ahead of the others, according to the annual review report from the European Maritime Safety Agency (EMSA) entitled “Annual Overview of Marine Casualties and Incidents 2024.” In the years 2014 to 2022, equipment failures accounted for 25.3% of maritime incidents, second only to those due to navigation, but

mainly through vehicular causes [1]. The statistics of failure of dedicated ships are of particular relevance. Analysis of operations of research vessels showed that 76.3% of surveyed specialists took part in expeditions that were broken from measurement and related electrical equipment [15]. This proves that even on vessels with a competent crew and up-to-date equipment, the reliability issue is not solved. The risk analysis established 12 overarching risk factors; despite natural forces, technical ones take precedence, highlighting the importance of implementing automated control systems. Data from offshore and Onshore Reliability reveal that, for underwater control systems, it is most widely reported that the common failure will be a signal failure, whereas electronic module failures should be considered to have the highest criticality ratio. [16] This corresponds to changes in the vulnerability vector from mechanical devices to digital management and information transmission ones.

A study of the reliability of generation systems on offshore patrol vessels revealed a worrying trend. The reliability of a power plant made up of four diesel generators was under 70% for the first 24 months of operation [17]. These results line up with the "bathtub curve," which describes the initial period of operation as a period of higher failure due to installation defects and running-in [18]. Utilization of ANNs found that the threshold load (approximately 200 kVA) dramatically escalates the probability of overheating as well as generator malfunction, allowing optimization of operational modes. The marine environment has unique environmental stresses for electronics, such as vibration, shock, humidity, and salt spray.

There is a need for an in-depth knowledge of these processes in order to interpret sensor data. Research into the impact of shock loads on marine electronics has revealed specific failure mechanisms at the microlevel [19]:

1. Solder materials such as SAC305 exhibit a significant reduction in strength and toughness at high strain rates, typical of wave shocks. This results in rapid initiation and propagation of microcracks in solder joints.

2. Plastic deformation of connectors. Insufficient thickness of the gold coating on the connector contacts can lead to permanent bending of the copper substrate under inertial forces, thereby interrupting the electrical circuit.

3. Stress concentration in packages. The corners of chip packages are sites of mechanical stress concentration, making them susceptible to cracking under storm conditions.

These indicate the necessity of monitoring systems that can detect high-frequency transients that can signal microsecond contact interruptions prior to full system failure. Diesel generators continue to be the main energy source. They are the primary method for diagnosis, usually relying upon thermodynamic parameters and vibration monitoring. But AI allows for a level of accuracy that was not possible before. A novel method to detect faults in marine diesel engines was presented in 2025 [20], which adopted Compressive Sensing and SqueezeNet deep learning models. The dimensionality of vibration data is too big compared to most of the traditional methods. The compressed sensing method allows effective data reduction without any information loss, and SqueezeNet, as a lightweight architecture, provides high performance to maintain high accuracy in fault classification even with varying engine speeds and a smaller base training sample size. This is particularly useful for limited resource-constrained on-board hardware systems. Another method [4] builds recurrence graphs (plots), constructed using vibration signals, and converts a one-dimensional time series into a two-dimensional image. Based on this image, CNN is trained to recognize the various stages of crankshaft bearing wear that could not be accomplished by classical spectral analysis.

Bayesian networks are also used to diagnose thermodynamic processes. A framework, also used in [21], incorporated ML anomaly detectors, EWMA (Exponentially Weighted Moving Average), and Bayesian diagnostic networks. This system permits detection of not just deviations (for instance, for any variation in exhaust-gas temperature rise); it can also

be used to find the cause behind it. For example, the model can distinguish, with a considerable rate of accuracy, if the rise in temperature results from a failure of a fuel injector in a cylinder or from an issue that extends to the entire air supply system (e.g., a charge air cooler contaminated). The IVY-RF algorithm (Random Forest optimized by the ivy algorithm) has demonstrated excellent performance for marine diesel engine fuel systems diagnosis [22]. 12 different fault categories were determined on this model, and 100% accuracy was achieved when using perfect data, even when 5% noise (that is typical of real ship conditions) was applied. The robustness of this method allows IVY-RF to be applied as a promising tool for automating decision-making systems.

The integration of wind turbines and solar panels into ship power systems creates new challenges for diagnostics. In hybrid systems, power converters are critical components. Failure of IGBT transistors can result in an instantaneous loss of generation. To predict such shortcomings, LSTM networks [5] have been proposed. LSTM networks analyze time-series data of three-phase currents and voltages, detecting subtle changes in signal shape that indicate thermal aging of the semiconductor crystal or degradation of the gate insulation.

Ship's transformers are exposed to significant vibration and thermal loads. Their diagnosis is mainly made based on dissolved gas analysis (DGA) and vibration monitoring. Conventional DGA (Duval triangle, Rogers ratio) interpretation methods often fail to make diagnoses on those problems that have multiple defects at the same time. Machine-learning algorithms like Random Forest (RF) and Decision Tree (DT) improve the accuracy significantly. In a study with 628 lubricant samples, the Random Forest model achieved diagnostic accuracies ranging from 95.2% to 100% on different types of thermal and discharge defects [23]. A second method, using correlation analysis and density-based spatial clustering of applications with noise (DBSCAN) to extrapolate DGA data, significantly increased the accuracy in fault clustering by 32.7% compared to the direct method [24]. This allows for the detection of defect initiation (e.g., local oil overheating) well in advance of gas protection.

Recent research suggests using the Transformer architecture and the Attention mechanism for transformer housing vibration analysis [25]. Mechanical deformation of the windings or weakening of the magnetic core layer changes the vibration spectrum. Deep learning models can automatically extract these features from the "raw" data, ignore the background

noise of the vessel, and classify the transformer state with high accuracy, even without prior expert signal processing.

Short circuits and arcing faults in switchgear are among the most dangerous accidents. Traditional current protections are often insensitive to high-resistance arc faults. Artificial intelligence enables the implementation of protection based on arc pattern recognition. In [26], the MTL-DNN (Multi-Task Learning Deep Neural Network) simultaneously addresses the tasks of accident detection, damage type classification (short circuit, overload, ground fault), and situation development prediction. The accuracy of diagnosing overloads and short circuits reaches 96.5% and 94.3%, respectively.

Fault localization is also essential. Algorithms based on traveling waves and condition assessment enable accurate determination of the location of a breakdown in a cable or busbar trunking, thereby minimizing search and repair time. [6]

Failure of the circuit breaker during a short circuit can result in a complete loss of power to the vessel. The leading causes of failure are contact wear and degradation of the drive mechanism. In [27], methods for assessing contact wear are compared. The "arc energy integral" method is commonly used but inaccurate due to the assumption of a constant arc-current shape. A more promising method is to measure dynamic contact resistance during the switching operation. Analysis of the DCR curve using ML algorithms allows for the estimation of the contact thickness and the degree of its erosion without disassembling the arc extinguishing chamber.

The current shape of the control solenoid coil (Trip/Close coil profile) analysis is a useful tool to diagnose mechanical components. Delays in armature movement and changes in the shape of current peaks indicate a sticking mechanism, spring weakening, or lubrication problems. This type of mechanical defect detection occurs through hybrid classifiers (SVM +

ELM), which can be used to determine such defects at an early stage with high accuracy [28]. Most ships still operate magnetron radars. Magnetrons have a limited lifespan and often fail suddenly. AI enables the prediction of the magnetron's remaining lifespan and planning to replace it before failure by measuring the emitted pulse spectrum and frequency stability. [29]

Conclusions. This research systematizes artificial intelligence methods for specific tasks in the diagnostics of ship equipment. Unlike existing general reviews, the work provides a cross-analysis of the physical nature of input signals such as vibration spectra, thermal parameters, oscillograms of arc processes, and the mathematical potential of modern neural network architectures within the Shipping 4.0 concept.

The research confirms that artificial intelligence has evolved from a theoretical concept into an effective tool for improving the reliability of ship equipment. Deep learning methods, specifically CNNs, LSTMs, and various modern Transformer-based ones, have outperformed the traditional methods in terms of technology development by offering a much higher prediction accuracy in marine systems with high noise and nonlinearity. Specialized solutions such as the Autoformer model can also achieve robustness to process non-stationarity. The outcome data tests with algorithms like IVY-RF for diesel plant diagnostics or MTL-DNN for electrical system protection have very high robustness and the detection of very complex fault types with nearly 100% precision. The integration of NLP technologies for unstructured documentation processing and expert systems for decision support creates a dynamic system analysis cycle that can be automated in real time. The ultimate idea for development can be that of hybrid systems, which offer a good balance between the practical aspects (physical models based on expert knowledge) and the freedom (flexible machine learning methods) to lower risk and keep maritime safety on the edge.

Bibliography:

1. Cicek K. Marine engineering systems failure analysis using extended failure modes and effects analysis with quality function deployment: maritime house of reliability. *International Journal of Quality; Reliability Management*, 2025. P. 1–23. URL: <https://doi.org/10.1108/ijqrm-05-2025-0157> (date of access: 13.01.2026)
2. Kalafatelis A. S., Nomikos N., Giannopoulos A., Alexandridis G., Karditsa, A., Trakadas Towards Predictive Maintenance in the Maritime Industry: A Component-Based Overview. *Journal of Marine Science and Engineering*. 2025. Vol. 13(3), P. 425. URL: <https://doi.org/10.3390/jmse13030425> (date of access: 13.01.2026)
3. Kottapalli, Siva, Hubli, Karthik, Chandrashekhara, Sandeep, Jain, Garima, Hubli, Sunayana, Botla, Gayathri, Doddaiah, Ramesh. Foundation Models for Time Series: A Survey. 2025. URL: <https://doi.org/10.48550/arXiv.2504.04011> (date of access: 13.01.2026)
4. Srinivaas A., Sakthivel N. R., Nair B. B. Machine Learning Approaches for Fault Detection in Internal Combustion Engines: A Review and Experimental Investigation. *Informatics*. 2025. Vol. 12(1), P. 25. URL: <https://doi.org/10.3390/informatics12010025> (date of access: 13.01.2026)

5. Kou L., Li, Y., Zhang F., Gong X., Hu Y., Yuan Q., Ke W. Review on Monitoring, Operation and Maintenance of Smart Offshore Wind Farms. *Sensors (Basel, Switzerland)*. 2022. Vol. 22(8), P. 2822. URL: <https://doi.org/10.3390/s22082822> (date of access: 13.01.2026)
6. Rezapour H., Jamali S., Bahmanyar A. Review on Artificial Intelligence-Based Fault Location Methods in Power Distribution Networks. *Energies*. 2023. Vol. 16(12), P. 4636. URL: <https://doi.org/10.3390/en16124636> (date of access: 13.01.2026)
7. Zhang S. Artificial Intelligence and Applications in Structural and Material Engineering. *Highlights in Science, Engineering and Technology*. 2023. Vol. 75, P. 240-245. URL: <https://doi.org/10.54097/9qknfc57> (date of access: 13.01.2026)
8. Chauhan V.K., Zhou J., Lu P. et al. A brief review of hypernetworks in deep learning. *Artif Intell.* 2024. Rev 57. P. 250 URL: <https://doi.org/10.1007/s10462-024-10862-8> (date of access: 13.01.2026)
9. Domrös-Zoungrana D., Rajaeen N., Boie, S., Fröling E., Lenz C. Medical Education: Considerations for a Successful Integration of Learning with and Learning about AI. *Journal of Medical Education and Curricular Development*, 2024. P. 11. URL: <https://doi.org/10.1177/23821205241284719> (date of access: 13.01.2026)
10. Hassaballah M., Awad A.I. (Eds.). Deep Learning in Computer Vision: Principles and Applications (1st ed.). *CRC Press*. 2020. URL: <https://doi.org/10.1201/9781351003827> (date of access: 13.01.2026)
11. Namdarian L. Towards AI-enabled evidence-based policymaking in science and technology: a conceptual framework. *Technology Analysis & Strategic Management*. 2025. P. 1–16. URL: <https://doi.org/10.1080/09537325.2025.2486003> (date of access: 13.01.2026)
12. Nikitha D., Imran Hussain S., Poornima M. Integrating Power BI with Machine Learning Models for Predictive Analytics. *2024 7th International Conference on Contemporary Computing and Informatics (IC3I)*. 2024. P. 1245–1250. URL: <https://doi.org/10.1109/ic3i61595.2024.10828685> (date of access: 13.01.2026)
13. Arnab Majumdar. Transformers for Time Series Forecasting. 2025. URL: <https://medium.com/@serana.ai/transformers-for-time-series-forecasting-e5e0327e78be> (date of access: 13.01.2026)
14. Oliveira J. M., Ramos P. Evaluating the Effectiveness of Time Series Transformers for Demand Forecasting in Retail. *Mathematics*. 2024. Vol. 12(17), P. 2728. URL: <https://doi.org/10.3390/math12172728> (date of access: 13.01.2026)
15. Kubacka M., Gajewski L., Burchacz M., Matczak M., Janowski P., Piotrowicz J. Many faces of survey equipment failures during marine research at sea—Risk analysis. *PLOS ONE*. 2022. Vol. 17(8), P. e0272960. URL: <https://doi.org/10.1371/journal.pone.0272960> (date of access: 13.01.2026)
16. Mahmoudi J. SIL analysis of subsea control system components based on a typical OREDA database. *Quality and Reliability Engineering International*. 2021. Vol. 37(8). P. 3297–3313. Portico. URL: <https://doi.org/10.1002/qre.2909> (date of access: 13.01.2026)
17. Daya A. A., Lazakis I. Component Criticality Analysis for Improved Ship Machinery Reliability. *Machines*. 2023. Vol. 11(7), P. 737. URL: <https://doi.org/10.3390/machines11070737> (date of access: 13.01.2026)
18. BĂJENESCU T. M. Reliability and Failures of Electronic Components. *Systems. Electrotehnica, Electronica, Automatica*. 2021. Vol. 69(2), P. 76–82. URL: <https://doi.org/10.46904/eea.21.69.2.1108009> (date of access: 13.01.2026)
19. Lang F., Zhou Z., Liu J., Cui M., Zhang Z. Review on the impact of marine environment on the reliability of electronic packaging materials. *Frontiers in Materials*. 2025. P. 12. URL: <https://doi.org/10.3389/fmats.2025.1584349> (date of access: 13.01.2026)
20. Radić J., Šarić M., Rubić A. Spectral-Based Fault Detection Method in Marine Diesel Engine Operation. *Sensors (Basel, Switzerland)*. 2025. Vol. 25(18), P. 5669. URL: <https://doi.org/10.3390/s25185669> (date of access: 13.01.2026)
21. Cheliotis M., Lazakis I., Cheliotis A. Bayesian and machine learning-based fault detection and diagnostics for marine applications. *Ships and Offshore Structures*. 2022. Vol. 17(12), P. 2686–2698. URL: <https://doi.org/10.1080/17445302.2021.2012015> (date of access: 13.01.2026)
22. Ouyang H., Li W., Gao F., Huang K., Xiao P. Research on Fault Diagnosis of Ship Diesel Generator System Based on IVY-RF. *Energies*. 2024. Vol. 17(22), P. 5799. URL: <https://doi.org/10.3390/en17225799> (date of access: 13.01.2026)
23. Al-Sakini S. R., Bilal G. A., Sadiq A. T., Al-Maliki W. A. K. Dissolved Gas Analysis for Fault Prediction in Power Transformers Using Machine Learning Techniques. *Applied Sciences*, 2025. Vol. 15(1), P. 118. URL: <https://doi.org/10.3390/app15010118> (date of access: 13.01.2026)
24. Liu Y., Song B., Wang L., Gao J., Xu R. Power Transformer Fault Diagnosis Based on Dissolved Gas Analysis by Correlation Coefficient-DBSCAN. *Applied Sciences*. 2020. Vol. 10(13), P. 4440. URL: <https://doi.org/10.3390/app10134440> (date of access: 13.01.2026)
25. Chen M., Gan H., Wu H. Research on Fault Diagnosis Method for Marine Diesel Engines Based on Multi-Scale Attention Mechanism Transformer. *Journal of Marine Science and Engineering*. 2024. Vol. 12(12), P. 2348. URL: <https://doi.org/10.3390/jmse12122348> (date of access: 13.01.2026)

26. Wan S., Kong Z. Fault diagnosis and prediction model of ship electrical system based on deep learning. *International Conference on Electrical Engineering and Intelligent Systems (IC2EIS 2025)*. 2025. P. 128. URL: <https://doi.org/10.1117/12.3069269> (date of access: 13.01.2026)

27. Li L., Wang B., Liu Y., Yu H., Zhang S., Huang M. Early Detection of Health Condition Degradation of Circuit Breaker Based on Electrical Quantity Monitoring. *Energies*. 2023. Vol. 16(14), P. 5581. URL: <https://doi.org/10.3390/en16145581> (date of access: 13.01.2026)

28. Sun T., Geng Y., Chen C., Yu Q., Yang L., Lu T. Static and dynamic contact performance of marine circuit breakers consider jolt vibration. *Electrical Engineering*. 2023. Vol. 106(3), P. 2785–2798. URL: <https://doi.org/10.1007/s00202-023-02110-z> (date of access: 13.01.2026)

29. King S. C., Tougher B., Zetterlind V. Estimating Speed Error of Commercial Radar Tracking to Inform Whale-Ship Strike Mitigation Efforts. *Sensors (Basel, Switzerland)*, 2025. Vol. 25(6), P. 1676. URL: <https://doi.org/10.3390/s25061676> (date of access: 13.01.2026)

Самойлов О.О. Дощенко Г.Г. МЕТОДИ ШТУЧОГО ІНТЕЛЕКТУ ДЛЯ ПРЕДИКТИВНОЇ АНАЛІТИКИ СТАНУ СУДНОВОГО ЕЛЕКТРОУСТАТКУВАННЯ

Метою цієї статті є аналіз та систематизація методів штучного інтелекту для прогностичної аналітики технічного стану судна. Потреба виникає через такі типи відмов технічного обладнання, які становлять понад чверть усіх інцидентів у морі. Наукова новизна цього огляду ґрунтується на відсутності комплексного аналізу найкращих архітектур нейронних мереж для прогнозування відмов таких критичних вузлів у морській галузі, наприклад, включаючи дизель-генератори та трансформатори. Ми розглядаємо, як розвивалися архітектури глибокого навчання, при цьому зростає важливість розгляду того, як увага використовується для аналізу складних часових рядів, від простих рекурентних мереж до сучасних трансформаторів. Зокрема, ми порівнюємо моделі *Informer*, *PatchTST* та *Autoformer*, підкреслюючи, що останні мають 38% підвищення точності прогнозування, досягнуте завдяки додаванню блоків декомпозиції трендів та сезонності. Було виділено переваги архітектур нейронних мереж (*LSTM*) порівняно з класичними статистичними моделями (*ARIMA*) для моделювання високовимірних даних у точному морському середовищі, такому як морські дані. Нарешті, ми представляємо новий метод виявлення несправностей дизельного двигуна на основі алгоритмів *SqueezeNet* та *IVY-RF*. Метод ансамблю випадкового лісу має точність аналізу розчиненого газу (95,2%-100%) у діагностиці трансформаторів. Далі ми описуємо використання багатозадачних багатопарових мереж завдань *MTL-DNN* для захисту електричної мережі від дугового утворення та метод аналізу зносу контактів вимикача без розбирання. Результати перевіряються за допомогою тестування. Підсумовуючи, внаслідок існуючих обмежень, майбутнє морської прогностичної аналітики полягає у створенні гібридних систем, які використовуватимуть динамічний аспект, що забезпечує метод машинного навчання, та предметні знання, які має користувач експертної системи, з метою підвищення безпеки та конкурентоспроможності судноплавства.

Ключові слова: штучний інтелект, предиктивна аналітика, *Shipping 4.0*, суднове електроустаткування, діагностика несправностей, моніторинг технічного стану, глибоке навчання, нейронні мережі.

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