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AUTOMATION TECHNOLOGIES IN SHIP SYSTEMS MAINTENANCE: PROBLEMS AND WAYS TO IMPROVE THROUGH CROSS-SECTOR EXPERIENCE

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The cross-sector borrowing of advanced automation technologies from the aviation, railway, automotive, energy, aerospace, and logistics sectors is considered to improve the reliability, safety, and efficiency of maritime transport maintenance. This study emphasizes the importance of transitioning from traditional scheduled maintenance to approaches based on actual technical condition and failure prediction. Based on a review of successful solutions in other industries, the article analyzes the possibilities of adapting the following innovations in the maritime industry: the introduction of equipment remote monitoring, digital twins, internet of things (IoT) sensors, diagnostic systems and machine learning for technical condition analysis, the use of drones and autonomous robots for inspection and emergency work, as well as the development of comprehensive digital maintenance management platforms. The article demonstrates that such technologies have already proven their efficiency in related sectors - reducing the number of accidents by 30–70%, reducing repair costs by up to 40%, and reducing downtime by 20–50%. At the same time, the maritime industry implements these approaches slowly, due to the lack of open databases for training forecasting models and the absence of unified standards for exchanging technical information. The paper emphasizes the need for a systematic approach to integrating predictive maintenance into water transport, creating a regulatory framework, developing a digital fleet infrastructure, and training personnel to work with new monitoring and analysis tools. The paper provides examples of already implemented initiatives, including remote monitoring of ships' engines, the use of certified drones for tank inspections, and analytical platforms for fleet maintenance management. It also describes potential future developments, such as repairing drones, autonomous firefighting modules, and digital ship health passports. The study's results indicate that implementing predictive maintenance can become a key direction in the digital transformation of the maritime industry. This will not only increase the reliability of vessels and the safety of crews but also significantly reduce operating costs, minimize environmental risks, and ensure a higher level of fleet readiness for modern challenges.
Keywords: *maritime industry, automation, cross-industry expertise, predictive maintenance, condition-based maintenance, remote monitoring, artificial intelligence, reliability.*

Statement of the problem

The modern maritime industry is facing challenges of increasing the reliability of ship equipment, improving transportation safety, minimizing accidents, and reducing operating costs. Despite the increasing complexity of marine systems, the pace of innovation in maintenance remains slow compared to other developed industries. High-tech industries, including aviation, railways, road transport, energy, and aerospace, have unique experience in implementing advanced automated monitoring, diagnostics, and predictive maintenance systems to increase reliability and safety [1, 2, 3]. The question arises: what technologies from these industries can maritime affairs borrow, and how will this improve monitoring, diagnostics, ensuring reliability, preventing errors and accidents, fault tolerance, emergency operations, technical inspections, and predictive maintenance in the fleet?

This article reviews the achievements of automation in related industries, presents quantitative results of their implementation based on research data, and analyzes the state of adaptation of these technologies in the maritime industry. The article pays particular attention to developing predictive maintenance, as the maritime industry has historically relied on routine maintenance and manual monitoring of the vessel's equipment, which is ineffective.

The relevance of the topic stems from the need for a rapid transition to digital, fault-tolerant systems that can reduce accidents and costs, while also ensuring a high level of safety at sea [4].

Analysis of the latest achievements on the identified problem

Numerous studies, discussed below, have already demonstrated the effectiveness of predictive maintenance (PdM), the Internet of Things (IoT), Big Data, and digital twins in related industries, including aviation, energy, transport, and logistics [2, 5, 6]. They indicate a significant increase in equipment reliability, a reduction in accidents, and cost optimization due to a combination of monitoring, diagnostics, and forecasting based on big data and artificial intelligence. Collecting large datasets from equipment and analyzing them can lead to a significant increase in reliability. Effects similar to those of aviation and railways, including 30% lower repair costs, 70% fewer accidents, and 40% less downtime, have become typical for enterprises that have switched to automated predictive maintenance in the energy sector [7].

However, in the maritime industry, such technologies are implemented fragmentarily, without unified standards and with significant barriers to adaptation [8]. However, there are isolated examples of the implementation of computer-based monitoring (CBM) systems and digital platforms (e.g., Wärtsilä, Rolls-Royce Marine) [9]; a comprehensive approach to integrating such solutions has not been established. There are no unified databases for training prediction models, no standardized interfaces for sensors and platforms, and no protocols, such as an automated storage and retrieval system (ASRS), for sharing incidents [5].

Unsolved problems include adaptation of cross-sectoral solutions to marine conditions, integration of autonomous diagnostic and emergency response systems, development of PdM models for key marine nodes, and automation of technical inspection without human intervention (robots, drones).

Purpose and task statement

The purpose of the work is to substantiate the feasibility and provide practical examples of implementing automation technologies from other industries into the maritime sector, thereby enhancing the reliability, safety, and efficiency of technical maintenance. The task is to conduct an interindustry analysis of effective automation solutions, identify mechanisms that can be adapted to marine technology, demonstrate existing examples of the implementation of such solutions in the fleet, and outline the prospects for the development of PdM in maritime transport.

Materials and methods

This study employs a qualitative methodology, grounded in a comprehensive literature review and a cross-sectoral comparative analysis. The research involved a systematic review of automation and predictive maintenance (PdM) practices from technologically advanced sectors, including aviation, railway, energy, and aerospace, drawing from scientific and industry publications.

Key qualitative data on specific technologies and quantitative data on their performance – such as reductions in costs, downtime, and accidents – were extracted and synthesized. A comparative analysis was then conducted, contrasting these findings with the current state of the maritime industry. This process identified opportunities and challenges for technology transfer and was used to substantiate the benefits of implementing predictive maintenance in the maritime sector.

Summary of the main material

Aviation is one of the most advanced industries in implementing automated equipment condition monitoring systems. Modern aircraft are equipped with thousands of sensors that collect engine, life support system, and airframe parameters in real-time. For example, Rolls-Royce has been using remote engine monitoring systems since the 1990s. The TotalCare program covers ~72% of Rolls-Royce aircraft engines and provides continuous data collection on their condition. This data is sent to ground diagnostic centers, where analytics detect deviations from the norm long before they lead to failure. Aviation was the first to introduce the concept of a continuous health and usage monitoring system (HUMS), which enabled the transition from periodic maintenance to condition-based repair.

The results of using such technologies in aviation are impressive. Aerospace and defense organizations that implemented predictive maintenance reduced maintenance costs by up to 30% and reduced the number of unscheduled repairs by 70%. Thanks to predictive strategies, airlines achieved a 25-30% reduction in fleet maintenance costs, a 70-75% decrease in breakdowns, and a 35-45% reduction in aircraft downtime. This is critical for airlines, as an hour of aircraft downtime can cost between $10,000 and $150,000. Diagnostic automation also enhances safety: early detection of problems has reduced the number of in-flight emergencies. According to Airbus, the implementation of predictive analytics systems reduces the number of unexpected failures in aircraft systems by 10-50% (with the most significant effects observed in air conditioning, power supply, and landing gear). Honeywell system Forge for APUs prevents ~35% of auxiliary power unit failures and eliminates up to 80% of flight delays associated with hydraulic failures. Thus, aviation demonstrates that comprehensive monitoring and diagnostics solutions (Big Data, IoT, ML) combined with predictive algorithms can radically increase the reliability of the aircraft fleet and avoid accidents through early intervention [3].

The aviation industry has also excelled in preventing errors and accidents by automating flight control. Autopilots and collision avoidance systems (TCAS) have long proven effective in minimizing the human factor. Thanks to automated control systems, modern commercial aviation has achieved an extraordinary level of safety, with fewer than 0.2 accidents per 100,000 flight hours. Aviation's experience in creating fault-tolerant systems (redundancy of critical components, automatic switching to redundant channels in the event of failures) has become a model for other industries. The high reliability of avionics and engines is achieved through both technical redundancy and continuous condition monitoring with automatic diagnostics [10].

Railway transport is also actively implementing automation to increase the reliability of rolling stock and infrastructure. A key area is the real-time tracking and monitoring of train conditions. In recent years, tens of thousands of sensors (including vibration, axle box temperatures, and geophones) have been installed on main lines, and specialized measuring cars utilize laser and ultrasonic scanning to inspect the track. This allows detecting defects (sags, rail cracks) before they lead to an accident, and planning repairs at a convenient time. Network Rail (UK) estimates that the transition to a world-class predictive and risk-based service can significantly reduce infrastructure maintenance costs, the number of failures, and unplanned downtime. Project OptRail, for example, uses fiber-optic sensors along the track (a technology borrowed from oil extraction) to continuously monitor rail stresses and provide early detection of the risk of track slippage or warping, improving safety and reducing the need for manual inspections [11].

Diagnostics of the train's condition while in motion are actively used. Sensors on cars and locomotives monitor the temperature of axle boxes, the condition of brakes, and pressure in systems. Data is transmitted to cloud platforms, where artificial intelligence algorithms predict the time until component failure. Predictive maintenance in the railway industry enables locomotives and cars to be repaired precisely when needed, thereby avoiding unnecessary maintenance and preventing sudden breakdowns during journeys. The implementation of predictive maintenance on the railway reduces maintenance costs by 10–40% due to schedule optimization and reduction of emergency repairs. Deutsche Bahn has already achieved 25% cost savings after implementing an AI-based infrastructure condition diagnosis system (KONUX system for monitoring switch points). This was achieved by minimizing downtime and maximizing network performance. In addition to cost savings, predictive maintenance enhances traffic safety: the timely repair of wheelsets or rails significantly reduces the risk of train derailments. As a result, automation enables rail operators to maintain a high level of transportation reliability: modern railways have virtually eliminated head-on collisions and serious accidents with the help of electronic systems and automatic blocking [2].

In the field of trucking, automation primarily aims to ensure traffic safety and prevent accidents, while also enhancing the reliability of fleets by monitoring the technical condition of trucks. Modern trucks are equipped with onboard computers and telemetry systems, which constantly collect data on the engine's operation, transmission, brakes, fuel level, and other key components. Fleet management systems (FMS) track the location and condition of each machine in real time and can automatically schedule maintenance when sensors indicate wear (for example, increased vibrations or bearing temperature). According to estimates by the US Department of Energy, implementing predictive maintenance can generally reduce the number of equipment breakdowns (including transportation) by 70% and repair costs by 25%. For auto parks, this means a sharp reduction in truck downtime on the route due to emergency breakdowns and, accordingly, an increase in the punctuality of cargo delivery.

The automotive industry is particularly focused on advanced driver assistance systems (ADAS), which prevent accidents caused by human factors. For example, the industry widely implements automatic emergency braking (AEB) and collision avoidance systems in trucks, and they have already led to a significant reduction in accident rates. The Insurance Institute for Highway Safety (IIHS) showed that cars with a front sensor and AEB had a 50% reduction in collisions with oncoming traffic (compared to vehicles without such systems). In other words, automatic braking helps to avoid half of potential «truck-on-vehicle» accidents. Lane-keeping systems, blind-spot monitoring, and driver fatigue warning systems also reduce accident risk. The EU estimates that a complete set of modern ADAS can prevent up to 40% of serious truck accidents.

In parallel, logistics companies are utilizing predictive maintenance for their parking facilities. For example, UPS and DHL delivery services have implemented analysis of truck sensor data, which has allowed them to detect signs of malfunctions (such as a drop in generator voltage or a tire pressure leak) before a breakdown occurs. This has enabled the reduction of sudden failures on the route and lower repair costs. However, specific figures are difficult to provide (due to commercial confidentiality). An additional factor is the reduction of fuel consumption, as monitoring systems optimize driving style and technical condition (for example, the timely replacement of air filters), which provides fuel savings of up to 5-10% [12].

Thus, in trucking, automation is two-faced: on the one hand, it prevents accidents through automatic intervention in control (such as braking and steering), and on the other, it maintains the reliability of equipment through continuous monitoring of the truck's condition and optimizes maintenance based on that condition.

Wind farms, especially offshore ones, operate in difficult-to-reach conditions, so the wind energy industry has actively implemented remote monitoring and diagnostics systems for turbines. Each modern wind turbine is equipped with a set of sensors that measure vibrations on the gearbox and bearings, generator temperature, oil pressure, and other parameters. Specialized software, supervisory control and data acquisition (SCADA), and machine learning algorithms send data from thousands of turbines to control centers, where they analyze trends and detect early signs of damage – for example, an increase in vibrations at a particular frequency can signal the onset of a crack in a gear tooth in the gearbox. Thanks to this, operators can plan a repair window in advance and replace a part before it fails, preventing the turbine from stopping. Practice has shown that a predictive maintenance system can reduce unproductive downtime of wind turbines by 20–30%, thereby increasing annual electricity production (availability) by several percent. Experts estimate that maintenance savings of up to 10% per year can be achieved through better planning and avoidance of emergency repairs. This is borne out in practice: for example, a 126 MW Italian wind farm reported significant reductions in operating costs and increased turbine availability after implementing fully digital control [6].

In addition to purely technical reliability, automation in wind power has allowed for the optimization of turbine efficiency. Continuous monitoring and real-time analysis of weather conditions and loads enable operators to immediately adjust the angles of inclination of the blades and the nacelle's orientation, thereby maximizing generation. Automatic control systems, such as SCADA controllers, perform these adjustments according to the specified algorithms themselves. As a result, large wind farms are now actually controlled automatically, and people only monitor the overall indicators.

Another technology in the wind energy arsenal is the use of drones for condition inspections. Previously, inspecting turbine blades (for cracks or icing) required stopping the turbine and lifting a person to a height of 100 m. Now, autonomous drones equipped with cameras fly around the blades, capturing high-resolution images, and computer vision programs identify even the smallest cracks. Thus, the automation of monitoring and predictive maintenance has become the standard in wind energy, enabling the economic maintenance of hundreds of turbines scattered at sea. Predictive maintenance has transformed wind farm maintenance from responding to breakdowns to planning in advance, minimizing emergency shutdowns and the associated losses [7].

Nuclear power is an industry with uncompromising requirements for reliability and safety, which is why very complex control and protection automation systems have been developed here from the very beginning. Each nuclear power plant (NPP) is equipped with thousands of devices that continuously monitor temperature, pressure, neutron fluxes, and other parameters of the reactor and turbines. Any deviations from the norm are automatically recorded, and the system immediately warns operators or initiates protective actions itself, for example, by emergency shutdown of the reactor in the event of overheating or activation of the shutdown control rod mechanism (SCRAM). A key principle of the nuclear industry is defense in depth, which includes prevention, monitoring, and action to mitigate the consequences. For example, to prevent accidents, all critical components at a nuclear power plant are designed with redundancy (triple redundancy of cooling systems and duplicate sensors for each parameter). If a failure does occur, other channels automatically take over the function – this ensures fault tolerance even in the case of single failures [13].

Over 60 years of nuclear power plant operation, global statistics demonstrate the effectiveness of such automated systems: with over 18,500 reactors in operation, only three major accidents have occurred. In other words, the probability of a serious accident at a reactor is extremely small – about 0.016% per year. Automated safety systems that operate before a person can react achieve this. Lessons from past incidents (e.g., Three Mile Island, 1979) have led to the introduction of even more advanced control systems, including computerized consoles and expert diagnostic systems that help operators interpret an avalanche of signals. The industry is also developing intelligent operator support systems – hybrid AI systems that analyze a large amount of information and suggest optimal actions for personnel to stabilize the regime. For example, in the event of an unusual situation (a rare combination of failures), such a system could offer a response scenario generated based on modeling, anticipating the development of the accident [14].

In terms of monitoring and diagnostics, the nuclear industry sets the highest standards. All NPP equipment undergoes regular automated checks, including valve self-diagnostic systems and tests of emergency diesel generators underload. Continuous monitoring of equipment at NPPs enables the detection of degradation (for example, a slow increase in pump vibrations) and the planning of its replacement during the next scheduled maintenance, without waiting for an emergency to occur. Thus, elements of predictive maintenance have been utilized for a long time. Throughout this period, control systems support the equipment, as NPPs operate continuously for ~1.5 years between stops for fuel reloading. The result is a very high availability factor. The average installed capacity utilization factor (capacity factor) for nuclear power plants in the United States exceeds 92%, which is significantly higher than in other types of generation. This means that nuclear power plants operate at full capacity most of the time without unscheduled shutdowns [15].

From nuclear power, the maritime industry can adopt a culture of the highest possible level of reliability and safety through automation. Of course, ships do not have the same level of redundancy as nuclear power plants. Still, the principles are similar: installing redundant systems (e.g., two independent steering gears), using constant monitoring of the hull (for corrosion and metal fatigue) with sensors, and robotizing dangerous operations (e.g., automated fire extinguishing systems that are triggered immediately upon detection of smoke without human intervention). The lesson of the nuclear industry: forecasting and prevention are cheaper and safer than responding to an accident, is certainly relevant for the maritime industry (where ship accidents can have catastrophic consequences – the death of the crew, environmental disasters in the event of oil spills).

Other energy sectors include thermal (coal and gas), hydro, and other forms of generation, as well as oil extraction and petrochemicals. In all these industries, automation is designed to maintain the continuity of equipment operation and reduce the likelihood of equipment failure and accidents. For example, the industry widely uses real-time gas turbine diagnostics systems in modern gas-fired power plants. NextEra Energy (one of the largest producers of gas and renewable energy in the US) implemented a system of 5000+ sensors on each turbine, connected to cloud analytics. ML algorithms process vibration, temperature, and exhaust gas composition indicators and predict failures 2–3 months in advance. The effect is a 23% reduction in unplanned shutdowns, resulting in annual savings of $25 million in repairs and penalties for under-produced energy. This is an example of how Big Data-based automation, Data, and AI directly impact the enterprise economy. Similarly, the oil and gas industry has long used vibration control systems for pumps, compressors, and drilling equipment. Predictive data analysis has enabled a significant increase in the availability rate of oil platforms and refineries, reaching 98-99%. For example, according to McKinsey, petrochemical companies reduce maintenance costs by up to 30% and increase equipment uptime by 5-15% thanks to predictive systems, which in total can bring the global industry up to $630 billion in savings every year [16].

The industry is also implementing innovative diagnostic systems in the field of energy distribution (electrical grids). Smart Grid networks utilize sensors on lines and transformers to detect overloads or impending failures, automatically switching power to prevent outages. Automatic frequency and voltage recorders record emergency modes in milliseconds and give a command to disconnect or start the reserve. Thermal power plants utilize digital twins of boilers and turbines–mathematical models that compare calculated and actual parameters in real-time and can detect, for example, heat exchanger degradation (by decreasing efficiency) or boiler slag buildup, even before generation decreases [17].

In the context of safety, the oil and gas industry, after a series of incidents (the explosion at Deepwater Horizon, 2010), has significantly enhanced the automation of emergency response: BOP systems (blowout prevention devices) now have multi-level automatic activation to shut down the well in the event of an accident, even if there is no operator command. Firefighting on platforms and the emergency shutdown of pipeline sections in the event of depressurization are all controlled by computers at a speed unattainable by a human.

The aerospace industry (including spacecraft, satellites, and rockets) operates in conditions where direct repair is not possible, so unique approaches to autonomous monitoring and fault tolerance have been developed. Each artificial satellite in orbit is equipped with a Fault Detection, Isolation, and Recovery (FDIR) system. Detection, Isolation, and Recovery is a set of hardware and software tools that automatically detect malfunctions, isolate damaged subsystems, and restore operability by switching to a backup or restarting the system. For example, suppose a satellite's gyro orientation sensor fails. In that case, the FDIR algorithm recognizes the incorrect data within seconds, turns off the sensor, and switches to the backup, all while simultaneously sending telemetry to Earth. Most satellites have backup on-board computers that are automatically activated when the main one fails – this protects the mission from failure in the event of a single failure [18].

Modern research spacecraft (e.g., NASA's Mars rovers) use elements of artificial intelligence to diagnose their systems for anomalies. If the electrical system emits non-standard signals, automatic diagnostics attempt to determine the type of fault according to built-in rules and, if possible, correct the situation, such as rebooting the controller or switching the power to another channel. NASA is developing hierarchical hybrid diagnostic systems for future spacecraft that combine model-based and knowledge-based approaches. Experiments have shown that such algorithms can diagnose a wider range of failures than traditional methods, thereby increasing the system's autonomy. This is critical, for example, for a mission to Mars, where the signal from Earth is 10-20 minutes away – the device must make decisions itself in case of malfunctions [19].

A well-known example of emergency response automation is the Apollo system. During the Apollo lunar missions, an automatic emergency rescue program was implemented in Saturn V rockets. If the missile got out of control, the automation shot the command module with the astronauts on parachutes. It became the prototype of modern crew emergency rescue systems (LAS) on rockets, which are triggered without human intervention in a fraction of a second. This is an illustration of the principle followed by the aerospace industry: automation must react faster than a human to save the mission or life.

Space agencies also extensively utilize digital twins and simulations for predictive maintenance. For example, engineers on Earth have a digital model of the International Space Station, which the latest data constantly updates. This allows them to predict when a stabilization gyroscope will fail – and to send a replacement in advance on the nearest cargo ship. Space technology is designed with fault tolerance in mind: «No single point of failure» – no single failure should lead to the loss of the device. Automated backup and rapid diagnostics systems achieve this principle, which maritime autonomous vessels must also consider.

In addition, automatic systems for refueling and servicing satellites in orbit are currently being developed: for example, the Orbital projects Servicing Units are robots that independently approach another satellite, dock, and perform manipulations (repair, refueling). Experimental missions have partially demonstrated such operations (MEV-1 successfully docked with the Intelsat communications satellite in 2020 and adjusted its orbit) [20].

So, the aerospace industry offers the maritime industry examples of complete autonomy and self-diagnosis.

Warehouse logistics has undergone a significant leap in automation over the past decade, marked by the widespread introduction of stacker cranes, autonomous forklifts, and conveyor systems. Although the primary goal is to increase productivity and the speed of cargo processing, warehouse automation has also had an impact on the reliability and maintenance of equipment. First, robots and conveyors are equipped with condition sensors that monitor the load on the engines, backlash of mechanisms, temperature, and other relevant parameters. This allows us to draw up a planned and predictive maintenance schedule: replace components before they fail, but not too early. According to the consulting company Westernacher, the transition from paper-based procedures to system automation in warehouses yields an average 25% increase in productivity, a 10–20% more efficient use of space, and a 15–30% reduction in inventory due to more precise management and reduced failures. In other words, a well-automated warehouse operates continuously, without delays due to breakdowns, and uses resources more efficiently.

Amazon's automated warehouses, where thousands of mobile robots deliver shelves, exemplify built-in fault tolerance: if one robot fails, the control system immediately reassigns its task to another. The faulty robot itself automatically drives to the maintenance area. Thanks to this, the order picking processes do not stop. Complete digital coordination achieves this flexibility – the central system is aware of the status of each robot and can restructure logistics in real-time.

In terms of safety and accidents, automation in warehouses has significantly reduced the number of accidents (falling shelves, forklift collisions). Robotic systems have sensors to avoid collisions; people in warehouses are equipped with personal transmitters, allowing robots to «see» them and adjust their speed accordingly. This analogy compares marine collision avoidance systems, but inside the warehouse.

Equally important, automation has enabled maintenance analytics: all robots and mechanisms log their downtime, errors, and uptime. Companies use this data to improve design and maintenance planning. For example, if a conveyor is frequently stopped due to engine overheating, an algorithm can recommend installing additional cooling or performing more frequent maintenance [21].

The maritime industry can also benefit from warehouse experience in robotic inspection and repair. Some modern warehouses already have robots that can replace a module on the line independently (when a malfunction is signaled, a robot technician is dispatched to change the conveyor motor). The maritime industry does not yet use this approach on ships, but in the future, emergency robots may be able to, for example, automatically patch a hole in the hull (install a patch) or reset a tripped circuit breaker. Logistics centers also widely use maintenance management systems: each node is assigned a «passport», and the system reminds engineers of scheduled inspections based on operating hours. This is also being transferred to the fleet – modern Fleet systems Management applies similar principles.

Thus, the logistics/warehousing industry has demonstrated the effectiveness of complete digitalization of processes, resulting in increased productivity and reliability of equipment, as well as reduced downtime losses. The maritime industry, which also includes warehousing operations (e.g., container terminals, ship holds), has already begun implementing port robots and management systems, drawing on this experience (e.g., the Rotterdam container terminal).

Adapting automation technologies in the maritime industry. By adopting best practices from other industries, the maritime industry has already begun its transformation.

Many leading shipowners have equipped their ships with remote monitoring systems for ship machinery, which feature dozens of sensors on key components, including main engines, generators, compressors, and pumps. These sensors transmit data in real time to shore-based technical support centers. For example, Rolls-Royce Marine (now part of KONGSBERG) has introduced the MarineCare service, an analogue of aviation TotalCare. The shipowner pays a fixed fee, and the supplier conducts ongoing monitoring and scheduled maintenance of its equipment. Already in 2014, each ship with a Rolls-Royce MT30 engine was supplied with 28 built-in sensors for online monitoring of its condition. SKF offers vibration monitoring systems for a ship’s shafts and propellers that warn of imbalance or wear long before an accident. These solutions have minimized unexpected breakdowns. According to reports from service companies, customers using constant monitoring are 50–60% less likely to encounter emergency failures of the main engine or propeller, as problems are detected in advance and eliminated at an early stage [9].

Condition-based maintenance (CBM) in the fleet, classification societies (DNV, Lloyd's Register, etc.) have introduced regulations that allow replacing some routine inspections with maintenance based on technical condition, provided that approved monitoring systems are in place. A ship equipped with a certified CBM system may undergo dock inspections less often if sensors confirm the satisfactory condition of the components. This encourages shipowners to invest in sensors and analytics. There are already examples of large tankers operating without unexpected repairs for over 5 years, performing all surveillance in a digital format with annual data submission to the class for analysis.

As for autonomous navigation and safety systems, almost all commercial vessels are equipped with ECDIS (Electronic Chart Display Information System) with routing functions, autopilots, and AIS (Automatic Identification System) for data exchange (Fig. 1). A modern ship's autopilot is a cybernetic system that can maintain a course and speed, considering wind, currents, and other environmental factors. This is not complete autonomy, but it does significantly alleviate the crew's workload. Collision avoidance systems, based on radar and AIS, can signal or even intervene (via the autopilot) to prevent an accident. Thus, the elements of automatic accident prevention are already in place. For example, if the watch officer falls asleep, a modern system will detect a dangerous approach to another vessel and raise an alarm or correct the course. This principle was borrowed from aviation TCAS and adapted for use in a maritime context [8].

Drones and robotic inspections are also being introduced. In recent years, classification societies have begun to approve the use of drones for inspecting ship hulls and tanks. For example, DNV and ABS have certified the technology for inspecting ballast tanks using drones equipped with high-definition cameras. The drone can fly inside the tank, inspect the condition of bulkheads, detect cracks or corrosion – all without the need for a person to be deployed in a hazardous space. Cyberhawk has completed a full inspection of 19 tanks on an oil tanker using drones, receiving class approval. This significantly increases safety (people are less likely to descend into confined spaces) and can be performed more frequently than manual inspections, so problems are noticed promptly. The industry is also introducing underwater drones, known as ROVs, to inspect the underwater portion of the hull and propeller steering group, eliminating the need for divers.

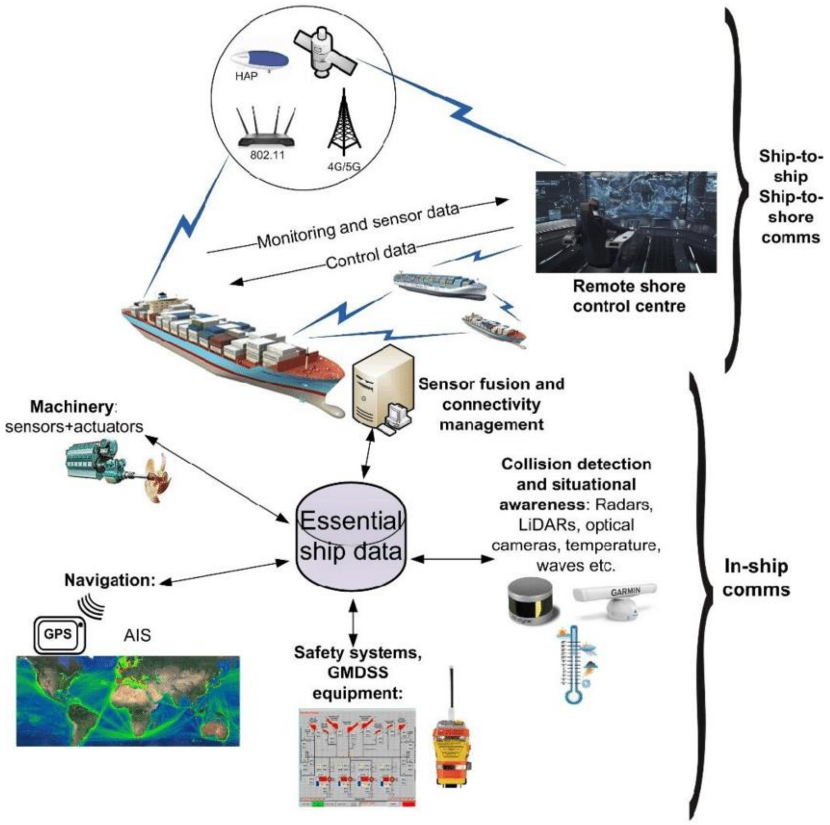

Figure 1 – CBM systems and digital platforms on a merchant fleet [22]

As for digital fleet management systems, most large shipowners use software packages for maintenance planning, spare parts inventory, and vessel status tracking (ShipManager, AMOS, Danaous). Integrated data received from vessels (via satellite) – engine performance, fuel consumption, alarm status is analyzed in a unified manner (StarConnect). This is a comprehensive step towards an intelligent fleet, where decisions are made based on data, not just the captain's intuition.

Regarding the automation of emergency work on ships. Drawing inspiration from logistics warehouses and nuclear safety, shipbuilders have begun developing robotic systems for emergencies. Gas analyzer robots that can move around the boat to search for the source of a fire or gas leak, and autonomous fire modules that navigate the hold and extinguish flames point by point. Such systems are not yet commercial, but prototypes exist. In the future, the ship's hull may have a network of built-in repair drones that can quickly patch small holes (using fast-hardening materials) or install a bandage on a leaking pipe. This is a development of the ideas of self-healing, inspired by both biology (the immune system) and NASA practice (a spacecraft should «heal» itself if possible).

Considering unimplemented or underdeveloped practices, the following can be distinguished:

- Crew Management, Resources Management, and pilot training from mistakes, in cargo transportation – fatigue warning. In the fleet, this is only developing;
- It makes sense to adopt the practice of sharing anonymous incident reports and designing system interfaces with the human factor in mind – similar programs (like ASRS in aviation) would help reduce accidents at sea;
- Stationary control points in the railway industry may also have an analogue – in shipping, there are nodal points (e.g., canals or straits) where scanners of passing hulls can be installed to detect damage or fouling;

Thus, the maritime industry is in a state of active modernization, implementing the achievements of «adjacent industries». Much of the above seemed like fantasy a few years ago (unmanned vessels, drone inspectors), but now it is already working or being tested.

As a separate conclusion, it is necessary to emphasize the importance of developing PdM of the fleet. Historically, ship maintenance was based on the planned preventive principle: after a set time or operating period, routine work was performed. This led to either excessive maintenance (incurring extra costs and replacing still serviceable parts) or insufficient maintenance when a failure occurred between scheduled routines. The transition to condition-based maintenance, utilizing sensors and analytics, enables the avoidance of both extremes. Modern large fleets – including tankers and container ships – already use data collection systems, but not all of them have learned to derive predictive value from this data. Therefore, one of the priorities is the creation of reliable forecasting models for marine equipment. For example, researchers are developing models to predict the remaining resource of propeller shaft bearings based on the vibration spectrum and oil temperature. Others are analyzing the electrical signals of generators to detect burns in the windings early. These efforts are gradually materializing in the form of software products that will be installed on ships or in shore-based centers.

Predictive maintenance provides not only an economic effect, but also a safety effect: a ship whose engine is serviced according to the actual condition is much less likely to lose its propulsion in the middle of the ocean. For the crew, this means less stress and risk. The already mentioned transition of most companies to PdM is expected to be the new norm in the coming decade. Imagine that the ship of the future sets off on a voyage with a "healthy" passport: all systems are in working order, and there is a forecast of when and which of them will require intervention. During the voyage, the system itself monitors the parameters; if something approaches the limit, it warns the team and the company to order a spare part to the port of destination. This is the ultimate goal – maximum fault tolerance through proactive maintenance. This transition is supported by classifiers: in 2021, DNV issued documents regulating the implementation of a data-based class («Data Driven Classification»), where the frequency of inspections depends on the actual condition.

Experience from other industries already shows that the maritime industry can achieve figures of a 2-6% increase in fleet availability, a 10-40% reduction in emergency repairs, and a 5-10% reduction in spare parts costs through optimization. Of course, the conservative maritime industry needs evidence and standards. Therefore, demonstration projects are underway: for example, Shell is conducting a PdM pilot project on its gas carriers, achieving reduced downtime and fuel savings. Such cases will gradually convince the market of the viability of new approaches.

Predictive maintenance can be seen as a key node where all innovations converge: sensors (IoT), connectivity, big data, and artificial intelligence, all for the purpose of predicting and preventing failures. The maritime industry, by integrating these tools, will enter a new era of reliability and safety, equal to the aviation and energy sectors. Everyone benefits: shipowners – from reduced costs and downtime, crews – from reduced emergencies, the environment – from fewer accidental emissions and spills. Table 1 provides a summary of best practices.

Table 1

Various best cross-industry practices and their adoption status

Best Practice	**Adoption status**	**Comment**
Remote monitoring systems	Adopted	Used for key machinery, such as engines and pumps. Example: Kongsberg's MarineCare service.
Condition-Based Maintenance (CBM)	Adopted	Classification societies permit the replacement of some routine inspections if certified CBM systems are utilized.
Autonomous navigation & safety	Adopted	Almost all vessels are equipped with ECDIS, autopilots, and AIS for navigation and collision avoidance.
Drone/robotic inspections (aerial)	Adopted	Drones are certified and used to inspect ship hulls and tanks, improving safety.
Digital fleet management systems	Adopted	Most large shipowners utilize software such as ShipManager or AMOS for planning and tracking purposes.
Predictive Maintenance (PdM)	In early transition	Expected to be the new norm, pilot projects by companies like Shell show reduced downtime.
Underwater drones (ROVs)	In development	Used to inspect the underwater portion of the hull, replacing the need for divers.
Crew & resource management	In development	Practices like fatigue warnings are still in the early stages of adoption in the maritime industry.
Robotic systems for emergencies	Not yet adopted	Prototypes for robotic firefighting and gas leak detection exist, but they are not yet commercially available.
Sharing anonymous incident reports	Not yet adopted	A proposed practice, like aviation's ASRS, to help reduce accidents at sea.
Stationary hull scanners	Not yet adopted	A proposed idea is to install scanners at choke points, such as canals, to detect hull damage.

Conclusions

The introduction of automation technologies from other industries into the maritime sphere is already yielding tangible results. The cross-industry exchange of engineering practices is a powerful driver of innovation in the maritime industry. Aviation teaches the sea to predict failures, IT teaches the sea to build fault-tolerant systems, railways teach the sea to control infrastructure remotely, and space teaches the sea to trust autonomous algorithms. The maritime industry has historically developed more slowly. However, now that it has absorbed these lessons, it is leaping towards a digital, automated future, where automation minimizes human errors and the reliability and safety of transportation reach unprecedentedly high levels.

The experience in aviation, rail, road transport, energy, logistics, and aerospace confirms that implementing automated monitoring, predictive diagnostics, and autonomous emergency systems enables significant increases in reliability, reductions in accidents, and cost savings.

Prospects for further research include standardizing the implementation of PdM across the fleet, developing digital twins of ships, examining the effectiveness of drones and robots for technical inspections, and establishing maritime technical incident sharing platforms, such as ASRS.

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ТЕХНОЛОГІЇ АВТОМАТИЗАЦІЇ В ОБСЛУГОВУВАННІ СУДНОВИХ СИСТЕМ: ПРОБЛЕМИ ТА ШЛЯХИ ПОКРАЩЕННЯ ЧЕРЕЗ МІЖГАЛУЗЕВИЙ ДОСВІД

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Розглянуто міжгалузеве запозичення передових технологій автоматизації з авіаційної, залізничної, автомобільної, енергетичної, аерокосмічної та логістичної сфер для підвищення надійності, безпеки та ефективності технічного обслуговування морського транспорту. Зроблено акцент на важливості переходу від традиційного регламентного обслуговування до підходів, що базуються на фактичному технічному стані та прогнозуванні відмов. На основі аналізу сучасних рішень в інших галузях, розглянуто можливості адаптації таких інновацій у морській індустрії: впровадження дистанційного моніторингу обладнання, цифрових двійників, IoT (інтернет речей)-сенсорів, систем діагностики та машинного навчання для аналізу технічного стану, використання дронів та автономних роботів для інспекції та аварійних робіт, а також розробка комплексних цифрових платформ управління технічним обслуговуванням. Стаття демонструє, що такі технології вже довели свою ефективність у суміжних секторах – зниження кількості аварій на 30–70%, зменшення витрат на ремонти до 40%, скорочення простоїв на 20–50%. Водночас у морській галузі ці підходи все ще впроваджуються повільно, що зумовлено нестачею відкритих баз для навчання моделей прогнозування та відсутністю єдиних стандартів обміну технічною інформацією. Підкреслено необхідність системного підходу до інтеграції прогнозного обслуговування у морський транспорт, створення нормативної бази, розвитку цифрової інфраструктури флоту, підготовки персоналу до роботи з новими інструментами моніторингу й аналізу. У роботі наведено приклади вже реалізованих ініціатив: дистанційний моніторинг суднових енергетичних установок, використання сертифікованих дронів для інспекції танків, аналітичні платформи управління обслуговуванням флоту, а також описано потенційні майбутні розробки – дрони-ремонтники, автономні модулі пожежогасіння, цифрові паспорти "здоров'я" суден. Результати дослідження свідчать, що саме впровадження прогнозного обслуговування може стати ключовим напрямом цифрової трансформації морської індустрії. Це дозволить не лише підвищити безвідмовність суден і безпеку екіпажів, але й суттєво знизити експлуатаційні витрати, мінімізувати екологічні ризики та забезпечити вищий рівень готовності флоту до сучасних викликів.

***Ключові слова**: морська індустрія, автоматизація, міжгалузевий досвід, прогнозне обслуговування, обслуговування за станом, дистанційний моніторинг, штучний інтелект, надійність.*

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