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Application of Artificial Intelligence in Marine Engine Control System: Recent Advancements

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ABSTRACT:

This thesis aims to find out recent advancements based on artificial intelligence (AI) in the field of marine engine control systems. The demand for using artificial intelligence in marine engine control systems is in growing phase to make the control systems more efficient, reliable and sustainable. This thesis explains the background of marine engine control system, including how conventional control systems work and what are their limitations. As the control systems are consistently moving towards artificial intelligence based algorithms, this thesis explores AI-based control systems, especially the ones which are related to marine engine control systems. The comparison between traditional control systems and AI-based control systems for instance, machine learning, fuzzy logic, and neural networks show which control system has better efficiency when it comes to optimized engine performance, fuel efficiency, and predictive maintenance. Traditional control methods are generally not suitable to handle complex situations in various dynamic conditions, real-time decision making, and predictive maintenance even though the methods are well established for a long period of time. This study also includes the positive impact of using artificial intelligence in various parts of control systems via discussing many case studies from real-world applications.

Despite the advantages of AI, the adoption of AI in marine engine control systems is not without challenges, including computational complexity and regulatory monitoring by authorities. This thesis concludes with a presentation of future trends in autonomous marine systems and AI integration, as well as with some key recommendations for future research and industry adoption strategies.

KEYWORDS: Artificial Intelligence, AI-based Control Systems, Conventional Control Systems, Engine Performance, Dynamic Conditions

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Abbreviations

AI	Artificial Intelligence
ML	Machine Learning
EFI	Electronic Fuel Injection
ECR	Engine Control Room
ECM	Electronic Control Modules
CNN	Convolutional Neural Networks
LPDF	Low-Pressure Dual-Fuel

1 Introduction

1.1 Background and Motivation

In practice, engine performance, engine control, and engine diagnosis are three main aspects of engine control systems. Engine performance refers to how efficiently an engine converts energy into usable power compared to others, considering factors such as emissions, fuel consumption, noise, mechanical, and thermal loads in speed-load conditions. Based on these aspects, engine control systems could offer innovative solutions while using advanced cutting-edge computer technologies such as fuzzy logic, expert systems, and artificial neural networks. These AI-powered methods offer reliability and flexibility than any traditional control models based solely on differential equations when handling complex and unknown operating conditions through real-time sensor data incorporated with domain expert knowledge (Antonić & Komar, 2007).

Similarly, Ineza Havugimana et al. (2023) mentioned, due to AI's ability to create and handle complex, nonlinear model without depending on physical presumptions, artificial intelligence (AI) algorithms integrated into control system have shown great potential for addressing issues with fuel economy, emission, and engine diagnostics. Charchalis & Pawletko (2011) also emphasized that, intelligent diagnostic systems, such as expert systems, that could be merged with knowledge from experts, diagnostic databases, and models of simulation are critical to achieve adaptive, effective marine engine conditions for ensuring ship safety and optimizing economic performance.

While working as a Commissioning Engineer, I have experienced the need for such an intelligent system that can act based on the critical sea situation. That is how my current job role has greatly influenced my choice of this topic for my master's thesis.

1.2 Problem Statement

The use of artificial intelligence (AI) in many different types of fields of operation is causing a rapid digital transition in the marine sector. However, the use of AI in marine engine control systems is still in its early stages, with several challenges, including the intricate nature of integration and lack of standardization. Additionally, these challenges have an impact in control system efficiency, safety, fuel efficiency and maintenance processes. Gradually AI implemented control systems to improve marine engine efficiency with their use of ML models becoming more popular, as they use predictive forecasting and automated control systems. AI could help to reduce downtime, increase efficiency of the control system and minimize overall expenses by using predictive maintenance and optimized real-time engine parameters.

Artificial intelligence and machine learning have shown high levels of potential in various domains, however, complex computing requirements, intricate data processing, and domain-specific modification requirements have kept them away from being widely used in marine engine control systems (Alexiou et al., 2021). Additionally, Asplund & Näslund (2022) mentioned that it is not always possible to check the practicality of those applications in dynamic environments as they tend to rely on simplified frameworks and lack real-world scenarios. Besides, marine officers tend to rely on control systems which are not fully AI-driven, as they feel more comfortable working with traditional control systems Lisowski (2021).

It is necessary to assess how developments in AI can be effectively applied to marine engine control systems in order to address these challenges and increase overall efficiency. This thesis will focus on the studies conducted in this domain in recent years and identify potential advantages and limitations. Additionally, a brief suggestion for future research will be presented at the end of this thesis.

1.3 Research Questions and Objectives

i. Identify and review the current AI technologies applied in marine engine control, including machine learning, neural networks, and predictive maintenance systems.

ii. Analysis of having AI-dependent control systems in improving fuel efficiency, real-time condition monitoring, predictive maintenance, and fault detection in marine engine control systems.

iii. Provide future research recommendations for increasing AI adoption in the marine industry.

1.4 Research Methodology

The thesis will follow a qualitative, literature-based approach, relying on secondary sources such as peer-reviewed journal articles, industry reports, and case studies.

- **Data Collection:** Data will be gathered through a comprehensive review of academic papers, industry publications, and reports on AI applications in marine engine control systems.

- **Data Analysis:** A thematic analysis will be conducted to identify key trends, challenges, and opportunities in the use of AI for marine engine control. Comparative analysis will be used to evaluate traditional control systems versus AI-based systems in terms of efficiency, safety, and reliability.

1.5 Scope and Limitations of the Study

The study is limited by its reliance on secondary data, as it is based on a literature review rather than primary data collection or empirical testing. As such, it does not provide experimental validation of AI technologies in real-world maritime environments. Additionally, the scope is restricted to commercial shipping, excluding other sectors such as defense or leisure marine industries.

2 Marine Engine Control Systems: An Overview

This chapter outlines the fundamentals of marine engine control systems, including traditional control methods like PID controllers, and their limitations. It also discusses technological advancement like AI-driven solutions and their efficiency in marine engine control systems management.

2.1 Fundamentals of Marine Engine Control Systems

Operators could be overwhelmed with unnecessary information while operating an engine control system as most of these are based on complex tools onboard. The goals of engine control systems are to maximize engine output, reduce fuel usage, and guarantee safe operation. Conventional methods traditionally rely on manual or semi-automated control, focusing on measured data and basic manual human dependent operation. In conventional methods engineers manually modify engine parameters like fuel injection timing, pressure, and temperature using mechanical gauges and direct observations in traditional marine engine control systems. Despite their efficiency, these systems posed the risk of inefficiency and human mistake due to their heavy dependence on human knowledge and intuition.

According to Ellenrieder (2022), a human dependent feedback system works with three key components: navigational observation by comparing GPS data in respect to the ship's position, making decisions based on the observations, and executing those decisions to control the ship's movement. Sensors, controllers, and actuators are used in machine-controlled systems to mimic these stages: sensing, control, and actuation. When the planned route deviates, the sensor picks it up and transforms it into a signal that the controller can understand. The controller makes the necessary adjustments to direct the actuator if it deviates from the planned route. This forms a closed-loop control system with more stability as shown in figure 2-1.

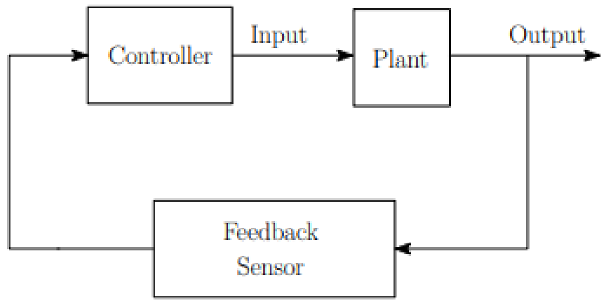

Figure 2-1 Stable closed-loop control system (Ellenrieder, 2022)

The semi-automated control systems were eventually implemented, incorporating basic electronic sensors and feedback loops to assist operators in maintaining optimal engine performance. However, these semi-automated systems have had similar issues with efficiency as they lacked data analysis and huge amount of human effort. According to Leach et al. (2020), even though traditional engine control systems were robust, they often lacked the capability of handling dynamic situations. With the development of marine technology, conventional control systems rapidly changed to include increasingly complex automation. Electronic control modules (ECMs) made it possible to regulate engine features like fuel-air mixture, ignition timing, and exhaust emissions with more accuracy. By processing sensor data using early microprocessors, these systems were able to make automatic adjustments in response to preset operating parameters. Despite these developments, their capabilities were still limited by fixed control algorithms that were unable to adjust dynamically to changing the quality of fuel, loads, or sea conditions.

However, recent advancements integrate artificial intelligence (AI) and expert systems to create more adaptive control systems. These new technologies provide a reliable method of engine monitoring and management by utilizing both unstructured information from experienced professionals and structured data from sensors (Gundogdu & Josefsson, 2020). Panyard (2024) reported in his university article, AI is being used by researchers at the Marine Engineering Lab at the University of Michigan to predict and prevent issues with ship gear, which is especially important for vessels that operate without onboard maintenance staff. AI helps optimize fuel efficiency and lower emissions in addition to safety and maintenance. Artificial intelligence (AI) systems can modify engine performance to mitigate environmental impact and increase fuel efficiency by evaluating large volumes of operational data. This is in accordance with the maritime sector's objective of using technological innovation to improve sustainability (Alshareef & Alghanmi, 2024).

2.2 Conventional Control Methods in Marine Engineering

PID controllers and similar mechanical devices are largely used in traditional marine engine control for controlling throttle adjustments, fuel injection timing, turbocharger speed based on sensor feedback and other basic parameters. These traditional approaches lack flexibility and adaptability, even though they are dependable in stable situations. Systems from large engine manufacturers, such as MAN and Wärtsilä, for instance, offer rudimentary diagnostics as part of full engine room management systems, but they usually need a lot of user input for more complex evaluations. This kind of dependency on fixed and rigid algorithms limits the capability to adjust its parameters in complex or dynamic conditions.

To minimize errors, the PID controllers can apply the changes by itself as they can compare the performance of the engine with any given desired setpoint. For example, fuel injection systems with PID controllers can make sure that the fuel has been properly provided at the correct time and amount to keep efficiency at high level and emission at low level. Besides, traditional hydraulic governors have been used to control power output and speed in marine engine control systems to achieve high and steady performance under varied conditions (Nielsen et al., 2021).

The Electronic Fuel Injection (EFI) technology has been adapted by major manufacturers such as MAN Energy Solutions and Wärtsilä to optimize fuel supply based on engine conditions in real time. According to Okazaki et al. (2005), emission of NOx and fuel consumption can be lowered down by 2-3% comparing to mechanical fuel injection when control system uses EFI technology. A similar example can be found in Wärtsilä's Low-Pressure Dual-Fuel (LPDF) system, where a marine engine can run on both LNG and diesel. The LPDF system precisely modifies fuel-air mixes by combining sensors and electronic actuators, guaranteeing seamless fuel type transitions without sacrificing efficiency. The LPDF system uses two modes, namely, Otto cycle in gas mode, where small portion of liquid fuel is injected to ignite an air-fuel mixture that reduces nitrogen oxide (NO_x), and other pollutant emissions. On the other hand, it switches to Diesel cycle during liquid fuel mode that offers reliability under dynamic conditions (gCaptain, 2013). The system itself is an attractive choice because of it meets IMO Tier III emission criteria standards without additional exhaust after-treatment. This also make the system environment friendly and cost-effective. Wärtsilä's 34DF engine is an ideal example of this, which has been widely accepted due to its ability to run on biofuels, heavy fuel oil (HFO), and LNG, ensuring operational flexibility in modern marine applications (Wärtsilä, n.d.). A key advantage of LPDF is its low-pressure gas admission, which requires supply pressure of up to 16 bar that lowers installation costs and simplifies onboard LNG handling. According to Modabberian et al. (2024), by integrating sensors and electronic actuators, the LPDF system precisely adjusts fuel-air mixtures, ensuring smooth transitions between fuel types without compromising efficiency. These illustrations show how traditional control techniques are essential in contemporary marine engine controlling when those are combined with electronic monitoring.

Marine engine control has two other important sub-systems- governing systems and engine load management alongside two basic one's fuel injection and propulsion control. For example, load-sharing systems effectively divide power across several engines in big ships, guaranteeing balanced operation and avoiding overloading. Mechanical governors in diesel engines have been widely used to automatically modify fuel supply in response to engine load, minimizing unnecessary fluctuations in speed (Modabberian et al., 2024). Additionally, ABB and Kongsberg have developed marine automation systems by integrating traditional PID-based controls with monitoring software to provide complete engine room management.

2.3 Challenges in Traditional Marine Engine Control

The maritime industry's growing reliance on automation, especially in Engine Control Rooms (ECRs), brings to light several issues, many of which are similar to those present in conventional marine engine control systems:

1. Limited Adaptability

Traditional marine engine control systems often rely on predefined diagnostic algorithms that are not capable of adjusting itself during dynamic operation conditions. The rigidity brings serious difficulties as the real-world marine applications often face variable loads, different types of fuels, and unpredictable weather conditions which require a more adaptive approach. According to Bainbridge (1983), automation frequently creates new problems rather than addressing old ones, necessitating more technological creativity. This problem is particularly noticeable in the engine control room (ECR), where complications arise if multiple vendor systems exist together. Demirel (2019) highlighted that these non-standardized interfaces cause issues for operators when they face critical situations on-board. Similarly, traditional systems to programmable electronic systems have adaptability issues. According to Wagner et al. (2009), engineers who used traditional tools had a greater overview than those who used PES. This suggests that although new technologies will provide several advantages, they still require significant design modifications to improve visibility and response.

Furthermore, it is often a problem to integrate critical machine learning features in traditional control systems. For example, predictive maintenance and fuel optimization are difficult for traditional control systems to incorporate. As AI-driven solutions continuously learn from its operational data, AI-driven control solutions have the potential to improve flexibility, unlike older technologies which lack these features in the control systems (Alamoush et al., 2024). This constraint emphasizes the necessity of updated control systems that use standardized communication protocols and adaptive algorithms. In addition to technological shortcomings, crew training and operational decision-making also face challenges because of limited adaptability. To ensure operational safety and efficiency, marine engineers and operators must regularly adapt to new control systems that are integrated with new automation systems (Grech et al., 2019).

2. Maintenance and Complexity

Lundh (2010) mentioned in her doctoral thesis that generally marine diesel engines diagnostics require high level human skill due to their variable load conditions. As the control systems are nowadays more automatic, it requires more focus in monitoring and troubleshooting the system instead of hands-on mechanical tasks. Because of this change, workloads have increased significantly for engineers, as new tasks, such as handling automation failures and administrative duties have emerged together. Additionally, as noted by (Demirel, 2019), the necessary knowledge base now encompasses electrical and electronic control engineering, an area in which present educational programs frequently fall short.

Traditional diagnostic tools, such as MAN's CoCoS-EDS and Wärtsilä's FAKS2i, mostly rely on predefined models. Even though these systems provide useful data interpretation skills, however, the rule-based algorithms often fail to process the data in emerging fault conditions or sensor discrepancies. Because of this limitation often expert opinions are required in novel or unforeseen cases which are caused by sensor malfunctions or software anomalies, when system itself is unable to make a decision. Consequently, engineers are forced to make workaround solutions, as often they don't get support from manufacturers, which increases operating expenses and prolongs maintenance times (Tuomala, 2021).

These challenges underscore the need for more flexible, AI-driven diagnostic methods which will not only rely on predefined models but also would be able to learn from the real-time data trends and capable of offering more robust solution for predictive maintenance. According to research, diesel engine fault diagnosis techniques have benefited from the use of artificial intelligence. However, convolutional neural networks (CNNs) haven't been thoroughly studied in the context of ship operation state data and small sample data. This shows how additional developments in intelligent diagnostic techniques could improve the accuracy and adaptability of identifying problems in marine diesel engines.

3. High Costs and Limited Use

Many ships, especially smaller ships are often reluctant to upgrade from traditional marine engine control systems because of the expenses required to upgrade and maintain. The costs for hardware, software, and training are often too high for many companies, which makes it financially unfeasible for them to change from mechanical to digital control systems. Often, the high capital expenses are the only reason why many smaller shipping companies tend to avoid the idea of implementing modern automation systems and rely on outdated mechanical systems in their engine control room. Delayed problem identification, higher energy consumption, and unnecessary maintenance costs are some important factors that have been faced by those outdated technology dependent systems. High cost, complexity, and lack of any standard protocol of modern technologies are the main reasons for their limited use. The number of vendors supplying electrical equipment for the ships have grown significantly over the past 20 years. Having many vendor’s devices makes it difficult for the engineers to successfully integrate one unified control system (Hynnekleiv & Lützhöft, 2020). One of the main reasons that prevents widespread adoption of these technologies are that the cost for installation and maintenance both are the responsibility of the owners. As a result, conventional vessels are running without having any real-time condition monitoring and automatic fault detection.

One way to tackle these challenges would be to integrate ongoing AI-driven predictive maintenance to improve adaptability by lowering down costs. According to Durlik et al. (2024), using AI-models to process operational data in real-time allows early fault detection and it helps in scheduling maintenance in an optimal way.

2.4 Technological Evolution in Marine Engine Management

Reduced emissions, increased efficiency, and more safety in marine industries are achievable by Autonomous marine vehicles (AMV). However, complex intelligent systems that incorporate cutting-edge control and diagnostic processes are necessary to achieve complete autonomy. Three critical technological advancements—**Expert Systems, Neuro-Fuzzy Models,** and **AI-Based Diagnostics and Predictive Maintenance**—are paving the way for improved marine engine management.

Expert Systems: Marine expert systems are customized AI applications focusing at replicating human expertise in marine-related areas. The systems are made up of two components: a knowledge base that contains information specific to the domain and an interpretation engine that uses logical rules on this knowledge to resolve complicated issues. For example, in ship design, an expert system can assess different design parameters and constraints to suggest optimal configurations, thus improving efficiency and safety. Expert Systems have significantly increased the diagnostic and control capabilities of marine systems. These systems allow modular and open design which allows knowledge base from the rest of the control system. Systems like CoCoS-EDS and FAKS2i demonstrate this method by keeping years of operational knowledge and utilizing rule-based algorithms to offer data-driven suggestions for fault detection and diagnostics (Coraddu et al., 2021). Figure 2-2 illustrates a general structure of the basic expert system. Consequently, figure 2-3 shows how an expert system would look like if it's integrated with a diagnosis system.

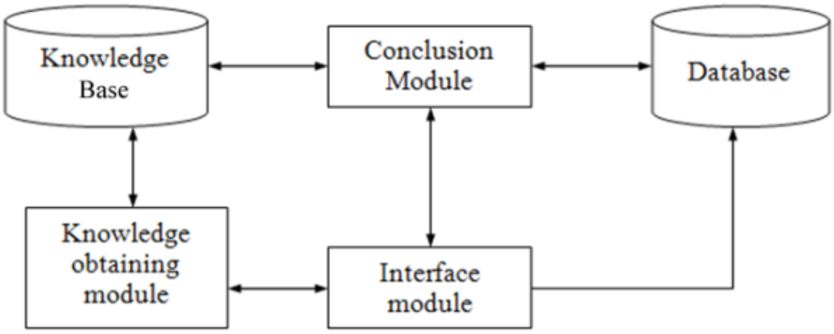

Figure 2-2 Basic structure of expert system (Charchalis & Pawletko, 2011)

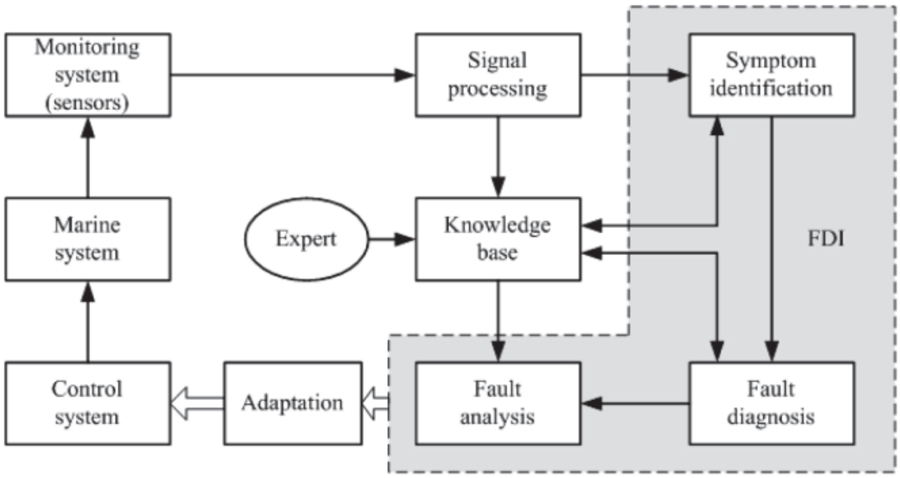

Figure 2-3 Expert knowledge-based control and diagnosis system (Antonić & Komar, 2007)

Neuro-Fuzzy Models: Kalogirou (2003) outlinedhow a general fuzzy model works without any input from neural networks. A basic operation of fuzzy controller works in a way that actual inputs are fuzzified and it makes those inputs as fuzzified inputs. Then those fuzzified inputs goes through a fuzzy processing which already has predefined set of rules and creates fuzzy outputs. At the end of the procedure fuzzy outputs goes through defuzzification and produce a real value for fuzzy output which is considered to be a controller output as well. This whole procedure has been illustrated in figure 2-4.

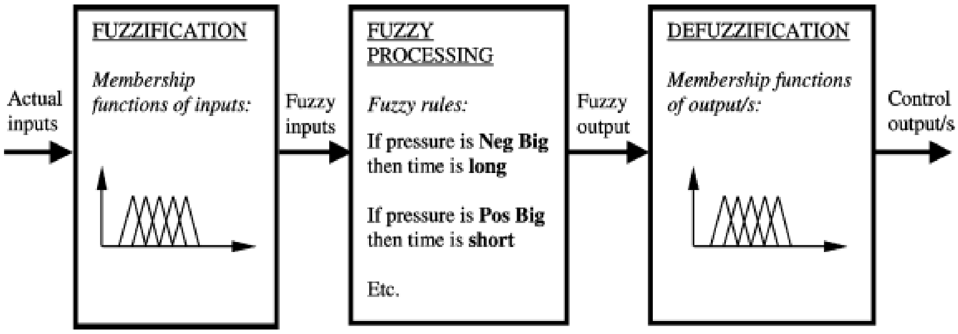

Figure 2-4 Basic operation of a fuzzy controller (Kalogirou, 2003)

On the other hand, with its modular design, the architecture of neuro-fuzzy model is scalable and adaptable, which allows the integration of various knowledge sources to address real-world complexities effectively (Skulstad et al., 2021). To handle incomplete or uncertain data Neuro-Fuzzy models can merge adaptive learning characteristics of artificial neural networks (ANNs) with fuzzy logic. Investigating engine parameters, for example cylinder pressure in different conditions can be achieved by using these types of models. Neuro-fuzzy models can learn from both historical data and real-time inputs, which they use when system needs adaptive control and real-time response due to operational changes in the system (Rath & Subudhi, 2020). These models are perfect for those challenging situations where both precision and adaptability are crucial.

Marine engine control system has adapted AI-based diagnostics and predictive maintenance to predict faults and activate preventive actions before any failure has occurred. Rule-based algorithm like MODLEM and EXPLORE has been in use with integration of expert systems for predictive maintenance applications. According to W. Zhang & Liu (2014) & Krishna Kumar et al. (2018), to minimize downtimes and increase overall engine reliability, AI-based algorithms can be used to identify abnormalities by using diagnostic database and operational data. By integrating expert knowledge, adaptive algorithm and real-time data manipulation it is possible to control complex marine engine control system, along with diagnostics and maintenance of the control system. Since reliability, efficiency, and safety of next-generation vessels comes with adapting these innovation, marine industry will have to keep itself updated with new technologies in this domain.

AI-Based Diagnostics and Predictive Maintenance: To improve operational productivity and safety traditional reactive methods have transformed to proactive methods by integrating artificial intelligence (AI) into marine engine control systems. Analysis of real-time data from engine sensors helps to determine potential faults early and prevent them from developing into major faults by using machine learning algorithms. An example could be seen from the collaboration between Magellan X and Neurons Lab, they have developed a solution for predictive maintenance by optimizing performances and energy efficiency. This project aims to gather real-time data from different equipment inside the ship and make a model that would be able to detect potential failure. This solution was primarily targeted to minimize downtimes of the system by analyzing each equipment data and eventually reducing maintenance cost.

Machine learning algorithms can also be used in evaluating the performance of onboard systems including analysis of data of all devices onboard. Fault patterns were identified by analyzing the sensor data onboard. Sweater cooling system of an oil tanker has shown how this kind of approach could work (Simion et al., 2024). This specific AI-based model worked in a way that human intervention was possible at the right time to achieve operational reliability and model could detect abnormalities well before it occurred. This kind of approach is important to determine how long a system can run without major issues or any human intervention.

An advanced AI-powered engine monitoring system has been deployed in Maersk Line vessels for development of a predictive maintenance models. This model gathers all real-time data from different types of engine sensors, such as temperature, pressure, and vibration measurements. Then the model generates a pattern which can suggest if there will be any equipment failures in coming time (Face, 2023). Eventually it allowed them to take decisions on maintenance schedules well before any actual failure happens.

These cases are few of those examples of having AI technologies into marine engine control systems in recent years.

3 Artificial intelligence in Control Systems

This section discusses about the application of intelligence control systems, specifically emphasizing on its role in energy management for marine engines. It will also cover AI methods like fuzzy logic, neural networks, and expert systems, and comparative analysis between traditional control systems and AI-based approaches both in general sectors as well as in marine environments.

3.1 Artificial Intelligence in Marine Energy Management Control Systems

Control systems have seen a transformation driven by artificial intelligence (AI), which makes it possible to make better decisions, be more flexible, and optimise in challenging situations. The rising complexity in modern industrial, automotive, and energy systems calls for more adaptable and intelligent control techniques. Traditional control system relies on precise mathematical models and predetermined rules to manage operations. By utilising data-driven technique learning from real-time inputs and generating accurate control choices under dynamic and unpredictable circumstances, AI-driven control systems provide several benefits (Carpanzano, 2023). When traditional methods are unable to handle complex state spaces, nonlinearity, and unexpected disturbance, the incorporation of artificial intelligence (AI) into the control system is very advantageous (Lau et al., 2022). Robustness is improved via fuzzy logic controllers and artificial neural networks (ANNs) which handle uncertainty and approximate nonlinear system dynamics. According to Matei et al. (2023), by constantly adjusting system settings AI-based optimisation methods like particle swarm optimisation (PSO) and genetic algorithms (GA) significantly enhance control performances. Figures 3-1 and 3-2 illustrate typical PSO algorithms and GA algorithms respectively. These techniques have shown increased effectiveness and operational resilience in industrial automation, robotics, and energy management (Halhoul Merabet et al., 2021). Intelligent, self-learning, and adaptive control approaches are made possible by the incorporation of AI into control systems, which is a major development in automation and engineering. The goal of ongoing research is to improve AI methods, so they are more interpretable, computationally feasible and data-efficient for mass industrial application (Kumar et al., 2024).

As highlighted by Vu et al. (2024) in their work an insight into the application of AI in maritime and logistics toward sustainable transportation, the incorporation of AI and ML into maritime operations is revolutionizing conventional methods, making them more intelligent and data-driven solutions. In addition to predictive maintenance, machine learning algorithms are utilized in fault diagnosis and health prognosis, essential for enhancing vessel reliability and operational efficiency. Shown in figure 3-3, fault diagnosis detects particular problems in machines or subsystems, thus enabling prompt action. Using both historical and real-time data, health prognosis estimates the remaining useful life of critical components, which leads to improved resource planning and lower operational costs. These applications considerably lower emissions, fuel use, and operational risks, in line with the sustainability objectives of the maritime industry.

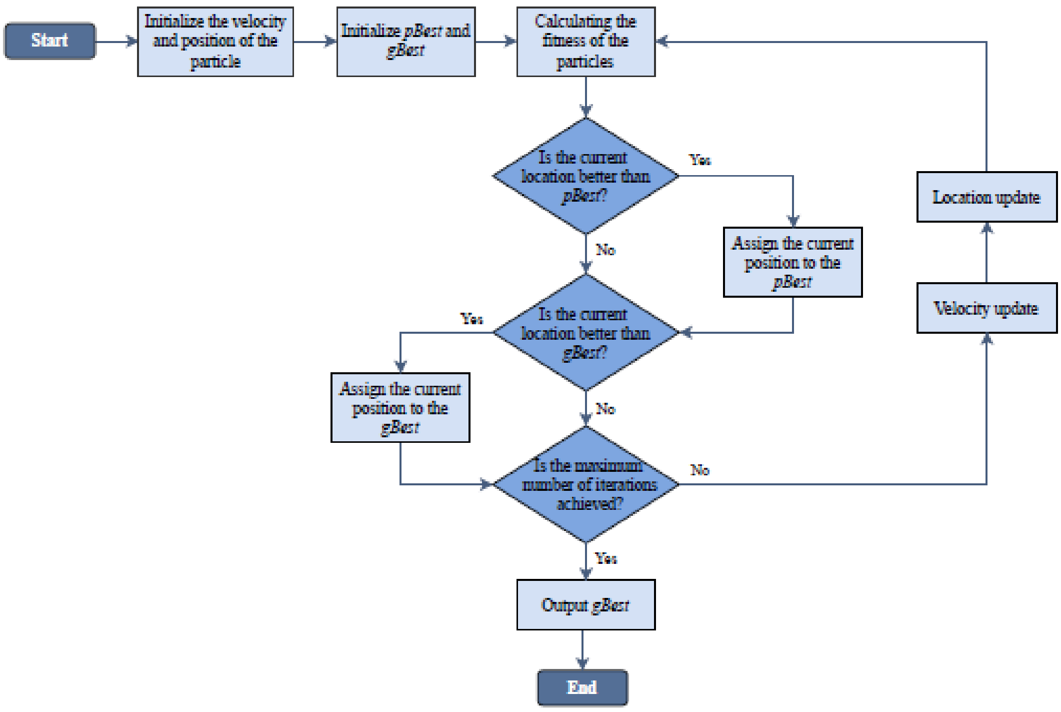

Figure 3-1 Flowchart of a conventional particle swarm optimization (PSO) algorithm (Matei et al., 2023)

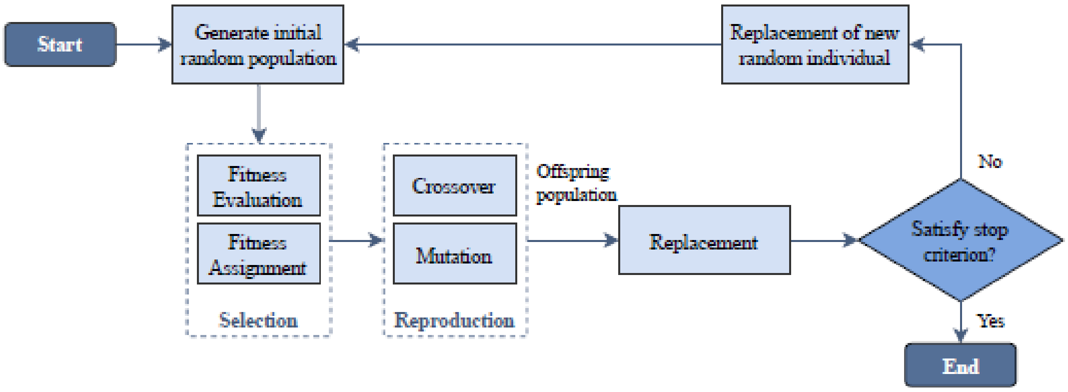

Figure 3-2 Flowchart of a conventional Genetic Algorithm (GA) (Matei et al., 2023)

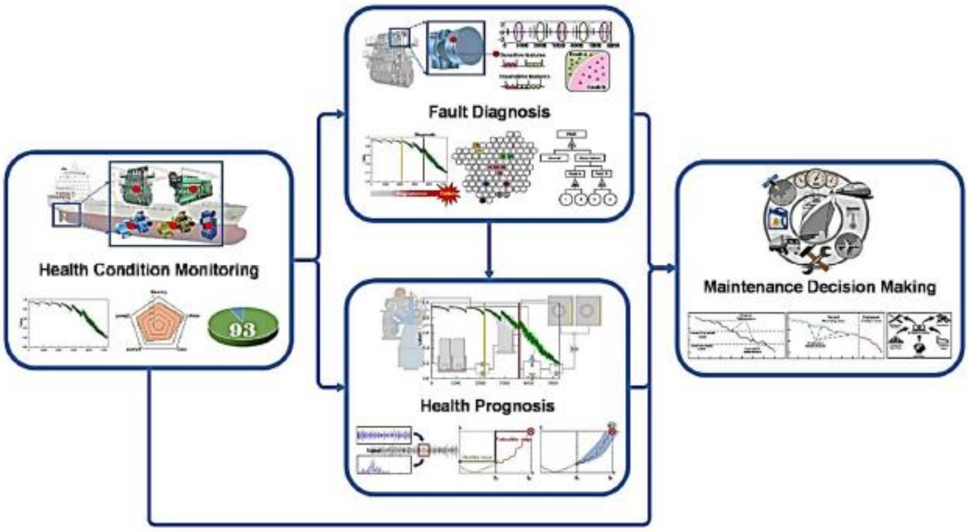

Figure 3-3 Applications of AI and ML in Marine Transport (Vu et al., 2024)

3.2 AI Techniques Relevant to Marine Engine Control (Expert Systems, Fuzzy Logic, Neural Network)

Figure 3-4 illustrates the categorization of ML techniques, demonstrating the application of supervised, unsupervised, semi-supervised, and reinforcement learning algorithms to different tasks like regression, clustering, and control. These models can analyze complex datasets to suggest proactive maintenance strategies, thereby minimizing both downtime and the possibility of mechanical failures (Vu et al., 2024).

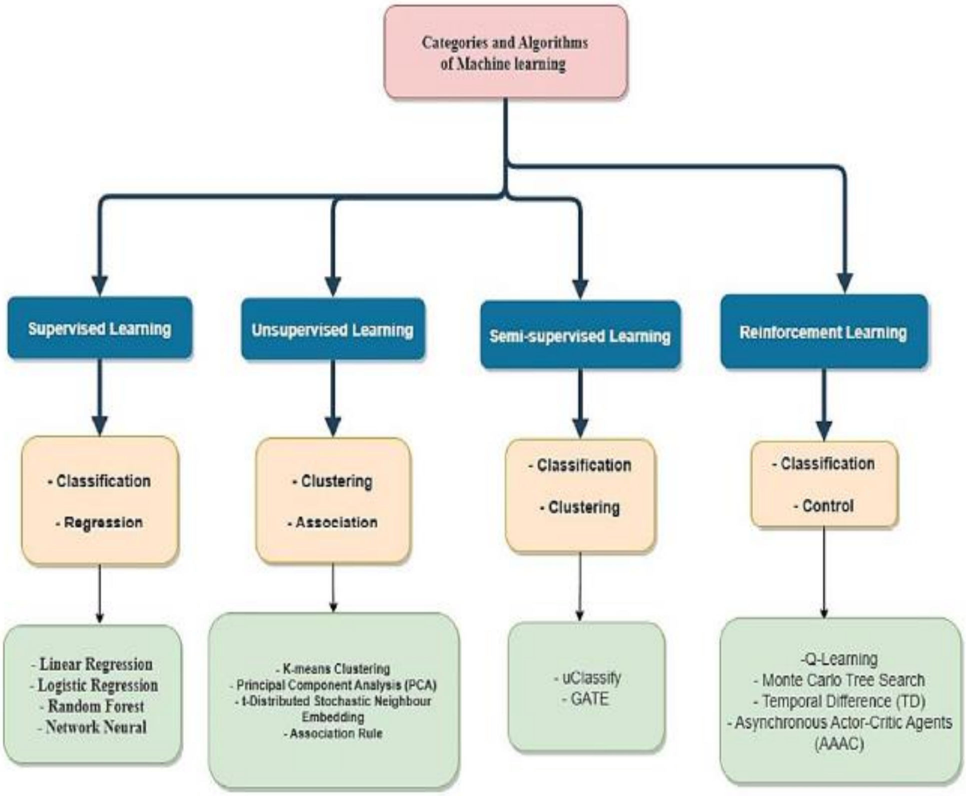

Figure 3-4 Overview of ML Techniques in Marine Transport (Vu et al., 2024)

AI-driven techniques, including expert systems, fuzzy logic, neural networks, are being used more and more for their ability to manage complex, nonlinear, and response to dynamic situations. An expert system is a computer program where computer software incorporates the expertise of a specialist in the field to solve problems or provide guidance. Thus, an expert system is a program that can imitate human intellectual skills such as problem solving, visual perception and language comprehension. An expert system includes a knowledge base, an inference procedure, an explanation section, and an acquisition component (Kalogirou, 2003). To get a result and conclusion to the problem, an inference procedure includes a method of how to process the present knowledge. The explanation section discusses the problem-solving method to the user. Finally, the acquisition component facilitates how the knowledge in the knowledge base is organised and used (Kalogirou, 2003). Patnaik et al. (2024) has shown in figure 3-5 how an expert system looks like during its operational phase with knowledge base, data processing and user interface.

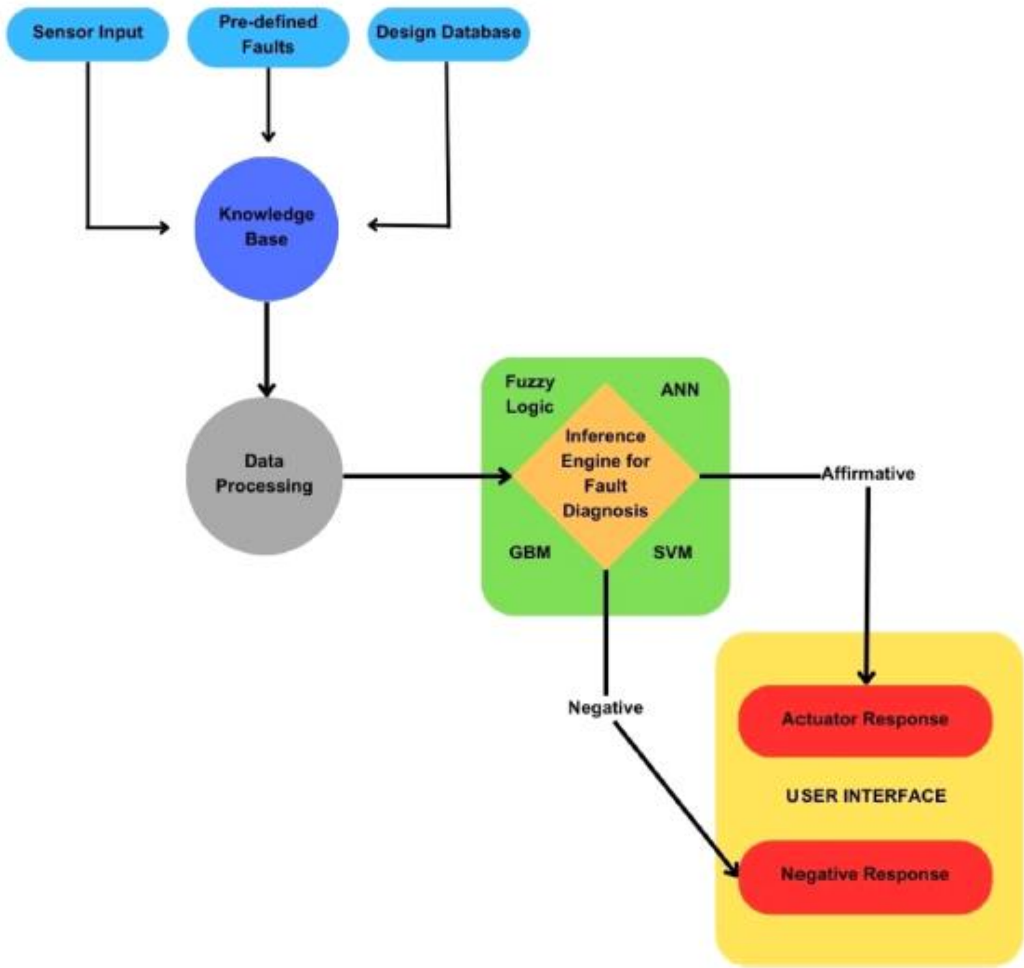

Figure 3-5 A whole operational phase of an expert system (Patnaik et al., 2024)

Same as expert systems, fuzzy logic provides accuracy and stability. Fuzzy logic controllers have been used in combination with optimization technique to make it feasible for achieving a more accurate, durable and adaptable control system. Figure 3-6 shows how a fuzzy logic control system generally works (Tran & Haidara, 2019).

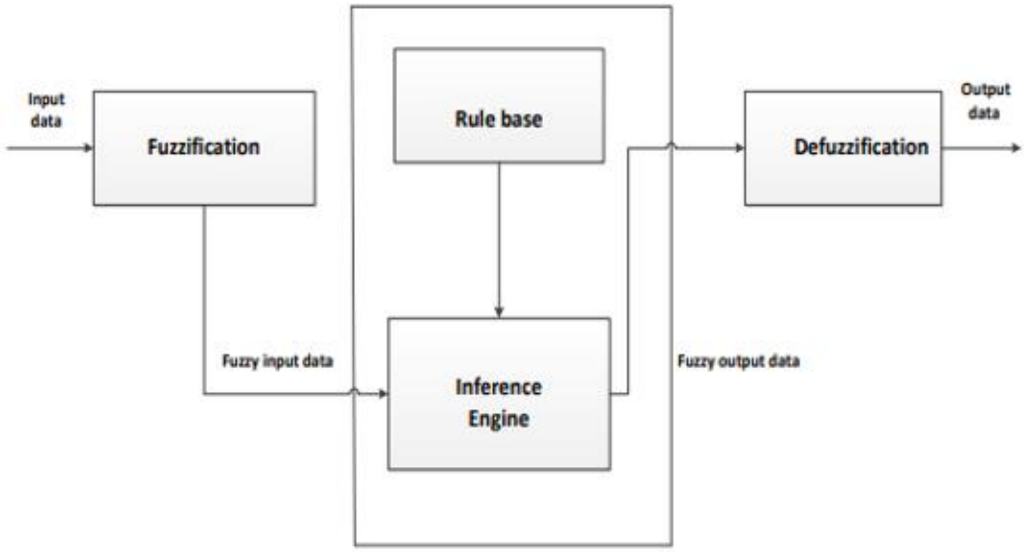

Figure 3-6 Block of Fuzzy Logic Control System (Tran & Haidara, 2019)

In their research, (Tran & Haidara (2019) compared between fuzzy logics and traditional Proportional-Integral-Derivatives (PID) for regulating marine diesel engine speed. Under dynamic condition, diesel engine speed could be controlled by simple membership function and “IF-THEN” fuzzy rules in an efficient way than a traditional PID controller with more robustness, adaptability, and reliability.

A study on speed control of diesel generator shows how fuzzy control outperformed traditional control method. The study was based on steady and transient speed regulations ratios of three control system: rigid feedback, constant speed feedbacks, and fuzzy control. The steady speed regulation ratio of the fuzzy control system was less than 2% but the rigid feedback systems had a steady speed regulation ratio of over 12%. The rigid feedback system's transient speed regulation ratio exceeded 8% but the fuzzy control systems transient speed regulations ratio was less than 4%. This illustrates how well the fuzzy control system performs (Wei et al., 2009).

The development of internal combustion (IC) engine has benefited immensely from the application of artificial neural networks (ANN) due to their ability to effectively design complex, nonlinear and dynamic systems’. Artificial neural networks handle vast number of datasets with the ability to learn from historical and real-time data, which makes it ideal for applications such as engine controls, faults detection, and optimizations. ANNs have been applied to optimize engine designs through analyzing multiple factors including emission levels, air-fuel mixtures and combustion efficiency. Figure 3-7 shows a machine learning based design process (Patnaik et al., 2024).

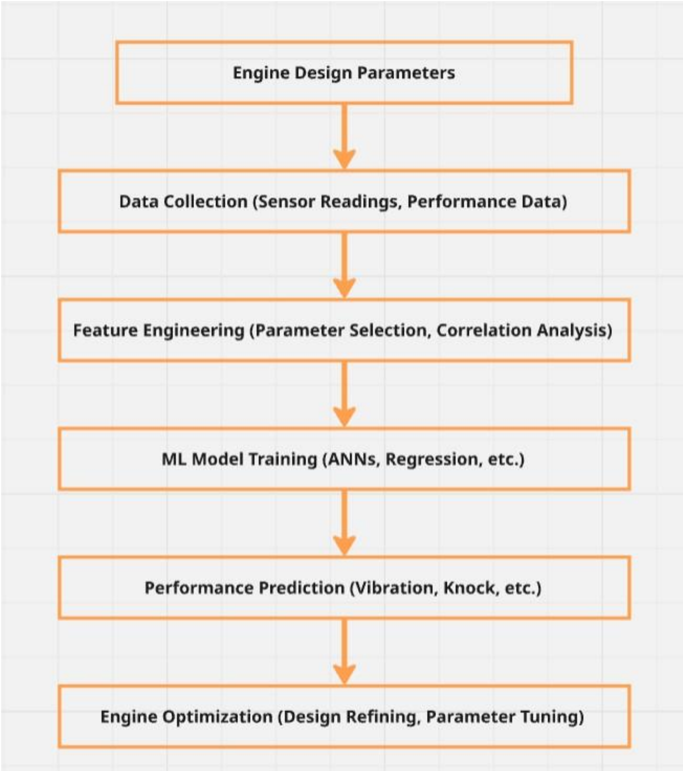

Figure 3-7 A design process, based on Machine Learning (Patnaik et al., 2024)

Automatic Radar Plotting Aid (ARPA) system for ship navigation also uses artificial neural network to improve its decision-making abilities. In this ANN's system subjective judgement of navigator and real-world scenarios are considered to design collision-preventing algorithms. By integrating neural networks into ARPA system it is possible to follow maritime safety rules (COLREGs) which considering the variables like tolerable trajectory deviation and manoeuvre advance time (Lisowski, 2023).

3.3 Traditional Control Systems Vs AI-Based Control Systems

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Conventional control techniques, which are based on classic concept like state-space representation and classical control theories, have long been essential to automation and industrial process. These strategies, which include adaptive control, optimum controls, and pole positioning, offer stability and resilience in well-known operating environment. Nevertheless, these systems may have trouble with intricate, nonlinear, or time-varying dynamic and often require precise modelling (Aström & Murray, 2010).

AI-based control systems on the other hand, use data-driven strategies and machine learning algorithm to learn from data and adjust to changes in conditions. Because of their flexibility they can deal with uncertainty and complexity that conventional approach might not be able to effectively handle. AI controller for example, may increase operational efficiency and product quality by optimizing processes in real-time. Many AI methods are model-free, which can be a drawback when used on real-time variable system, since it may not provide the same level of stability as conventional control techniques (Ellenrieder, 2022).

The ability of AI-based controller to analyse vast amount of data in order identify patterns and make reasonable decisions instantaneously is a major benefit. When system dynamics are too complicated for conventional modelling tools to convey such ability is very helpful. For instance, AI approaches have been used to improve controller performances in power converter-based systems, increasing reliability and efficiency (Gao et al., 2023).

But there are several difficulties in incorporating AI into control system. The interpretability of AI model is one of the main issues. Since many AI algorithms—particularly deep learning model—function as "black boxes," it might be challenging to comprehend how decision will be made (Bereska & Gavves, 2024). The computational complexity of AI algorithm is another difficulty. AI model implementation and training can be costly in terms of using large amount of electricity and processing capacity.

3.4 Traditional Control Systems Vs AI-Based Control Systems in Marine

According to Michel et al. (2024), traditional control system in marine engine heavily relies on programmed guideline, scheduled testing, and responsive techniques to solve issues when problems arise. Generally, the performance of diesel engines control systems depends on manually calibrated and defined parameters. To modify parameter like fuel injection time, air-fuel ratios, and exhaust gas recirculation (EGR) rates, these systems often use feedback loop, such as PID controller (Naradasu et al., 2013). According to Lazakis et al. (2010), the development of control systems in marine engineering is similar to the advancements of ship maintenance procedures. Like early maintenance technique, traditional control systems have mostly relied on rule-driven techniques, predictive model, predetermined limitations, and operator interaction. Reliability Centered Maintenance (RCM), Risk Based Inspection (RBI), and Condition Monitoring (CM) are few techniques that reflect these approaches, where faults are mitigated via scheduled inspection and fixed remedial measures.

Even though traditional systems are effective at ensuring basic operational reliability, however, they often fail to adapt if the conditions are dynamic or any unanticipated breakdown. This happens because instead of relying on real-time data, traditional system generally depends on fixed schedules, historical data which can result in inconsistencies, unplanned downtimes or even higher operational cost Michel et al., 2024). For instance, the conventional ship maintenance modes of planned maintenance

(PM) and corrective maintenance (CM) have growingly drawn attention to the disadvantage of “over repair” and “missing repair”, which have resulted in higher operating expense (P. Zhang et al., 2022).

Consequently, traditional control systems are prone to vulnerability which eventually leads to poor efficiency could be seen in any dynamic situation in running vessels when several interdependent variables affect engine performances (Naradasu et al., 2013). Additionally, PID controllers, heuristic-based tuning, and basic fault detections method generally govern the performances of marine engine control systems which are only effective in steady condition and lack adaptability to dynamic operating conditions (Lazakis et al., 2010). Traditional response systems often depend on human involvements which can cause delay and enhance the possibility of making mistakes under stressful circumstance.

On the other hand, recent studies have shown how AI-driven methods are effective in predictive maintenance and fault diagnosis for marine engines. According to Maione et al. (2024), real-time sensors data and machine learning algorithm are used in AI-based predictive maintenance (PdM) to evaluate the actual conditions of the parts of the engine and predict any breakdowns before they occur. This condition-based approach increases safety by minimizing random failures, optimizing maintenance schedules, and improves dependability. AI-powered systems increase overall efficiency of the engine by reducing idle times through continues monitoring of engine parameters.

Decision-making and flexibility have also enhanced when AI-based control techniques and machine learning are used together. AI-driven method increases the operational lifespans of marine systems and support more economical and sustainable maritime operation by switching from fixed control mechanisms to adaptive, self-learning models. In addition to predictive maintenance, cutting-edge methods like artificial neural networks (ANN) and support vector machines (SVM) use AI-based control systems to model complex links between engine parameter and performance indicators. By dynamically modifying control setting in response to data from sensors these technologies optimize fuel consumptions, improve performance, and proactively prevent failures.

4 AI-Driven Advancements in Marine Engine Control

4.1 AI for Predictive Maintenance and Monitoring

Predictive maintenance minimises operational downtimes, optimises maintenance schedule, and predicts problems by utilising AI-driven findings. This method is an enormous shift from traditional preventative maintenance, which depends on set service intervals and frequently result in unplanned breakdowns or unnecessary maintenance expenses. AI-based predictive maintenance can be divided into six fundamental components: data processing, AI algorithms, decision-makings, communication and integration, and user interface and reportings, as illustrated in figure 4-1 (Ucar et al., 2024).

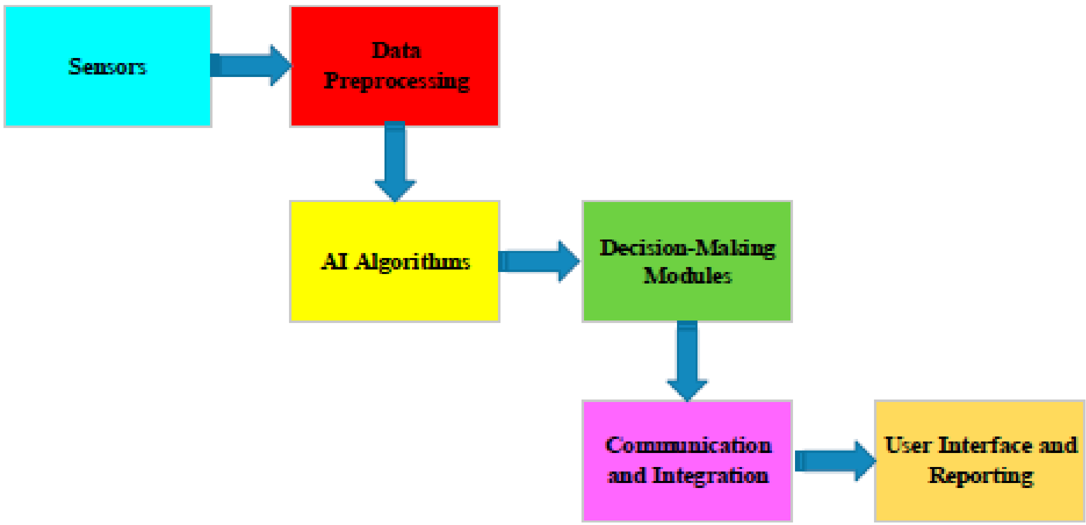

Figure 4-1 AI-based PdM system architecture (Ucar et al., 2024)

Advanced artificial intelligence algorithms are used to analyse data to foresee potential breakdown in equipment's and enable prompt maintenance actions based on that. Decision-making modules evaluates the degree of detected issues with recommendations of corrective actions. Communication is crucial as the smoothness of operation between onboard systems and shore-based facilities depends on that. Finally, user interface and reporting tools are used for advanced decision-makings (Simion et al., 2024).

By improving the scheduling and handling of maintenance duties, artificial intelligence (AI) significantly contributes to predictive maintenances in marine transportations. AI algorithms can optimize repair schedules and make sure that essential inspections are not missed by analysing previous inspection and maintenance data which lowers the chances of equipment failures. In addition to onboard uses, AI helps shore-based inspectors with Port State Control (PSC) inspections which are essential for maintaining environmental protections, marine safety, and seafarers' working conditions. Based on variables including ship age, kinds, flags, and past inspections data, predictive models such the balanced random forest (BRF)—are being created to forecast ships detention. By addressing the issue of unbalanced datasets in PSC records, these models increase safety precautions and anticipates vessel detentions with more accuracy. The marine sector can improve risk managements and expedite maintenance procedures by integrating AI into shore-based and aboard operations, which will ultimately result in safer, and more effective maritime operations (Durlik et al., 2024). Figure 4-2 shows how PdM can be integrated in AI-based marine transport system.

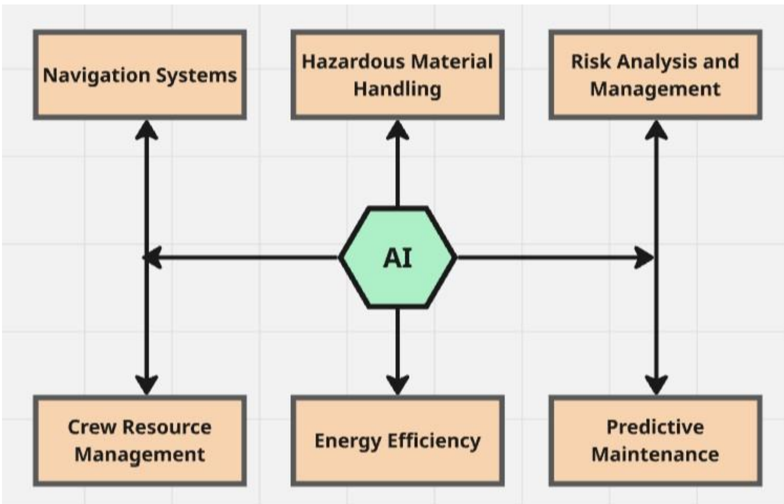

Figure 4-2 Maritime transport systems (based on AI) (Durlik et al., 2024)

Real-time monitoring systems powered by AI are revolutionizing marine operations by offering constant insight into environmental conditions and vessel performances. The Enterprise Remote Monitoring Version 4 (ERM v4) software for example has been installed aboard the USS Fitzgerald, a destroyer in the U.S. Navy. It uses machine learning to analyze more than 10,000 sensors signals per second from different ship components. This system ensures ongoing operational readiness by anticipating maintenance concerns and facilitating preventative measure (Harrington, 2025). Furthermore, operational dashboard with AI integration provides real-time insights into a range of vessel performance metric including as fuel consumption, emissions, crew productivity, and route management. This helps decision-makers make well-informed decisions and promptly adjust to shifting circumstances (Pannell & Mark J., 2024). AI-based visual systems also enable real-time vessel monitoring by operators, assuring adherence to operational and safety norm. AI identifies dangerous behaviour in onboard camera video feeds, and promptly notifies the crew. These developments support the growth of autonomous marine operation in addition to improving efficiency and safety.

4.2 AI-Based Fuel Efficiency and Emission Control

To keep the environmental effect at minimum level while maximizing the performances, modern engine control systems use AI-based algorithms for emission reductions and increase fuel efficiency. To forecast and optimise fuel uses, artificial intelligence (AI) methods use machine learning algorithms like support vector machines (SVM) and artificial neural networks (ANN).

Improved fuel economy forecasts and real-time engine performance optimization are made possible by neural networks’ exceptional efficiency in capturing nonlinear relationships. These models use a variety of input factors such as air mass flow rate, engine speeds, and throttle positions to create predictive models that help dynamically modify engine configuration for maximum fuel efficiency. AI-powered techniques are essential for emission controls as they are able to modify engines’ operating parameters which include carbon monoxides (CO) and nitrogen oxides (NOx). Although emissions are a natural byproduct of combustions, AI algorithms can still find the best combination to reduce their effect while keeping the performance requirements intact.

The accuracy of SVM models is improved when various input parameters are used such as the vehicle speed mass air flow (VS MAF)-based equations combined with the RPM throttle position sensor (TPS)-based equations as opposed to using a single input parameters (Ineza Havugimana et al., 2023). Recent developments in SVM optimisation techniques have enhanced its prediction performances despite some early limits when used to small dataset. As a result, it is now a useful tool in AI-driven engine management and figure 4-3 shows how a SVM & RPM-TPS equations based proposed model would look like.

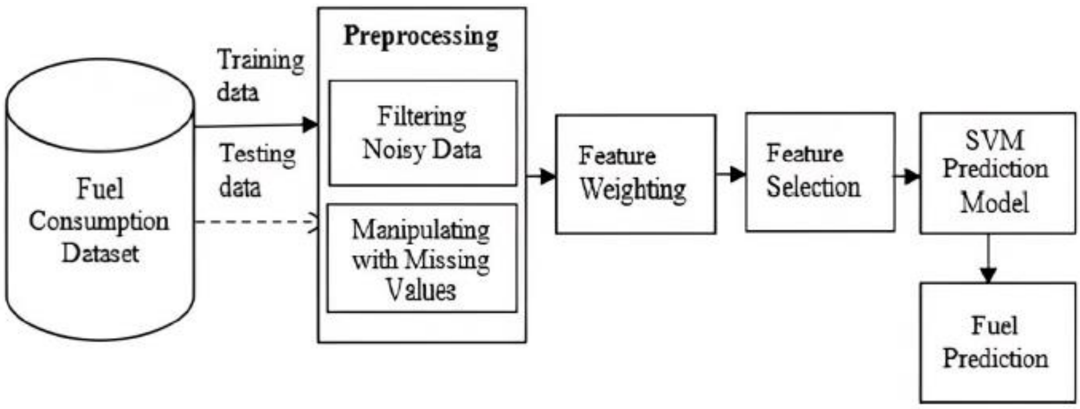

Figure 4-3 Proposed model based on SVM & RPM-TPS equations (Ineza Havugimana et al., 2023)

The selection of kernel functions and the calibre of training data determine how well SVM forecasts fuel usage. Better fuel efficiency estimates across various engine settings and driving conditions are made possible by SVM's ability to transfer the input variables into a higher-dimensional space, which allows it to capture nonlinear correlations unlike traditional regression models.

Consequently, the same author(s) proposed another two neuro-fuzzy models- Adaptive Neuro-Fuzzy Inference System (ANFIS) and Dynamic Evolving Neuro-Fuzzy Inference System (DENFIS) for their robustness in handling sensor data with huge amount of noise and reduce overfitting to enhance predictive accuracy of the model. These two models are generally implemented with Genetic Algor (GA). Their proposed model looks like figure 4-4.

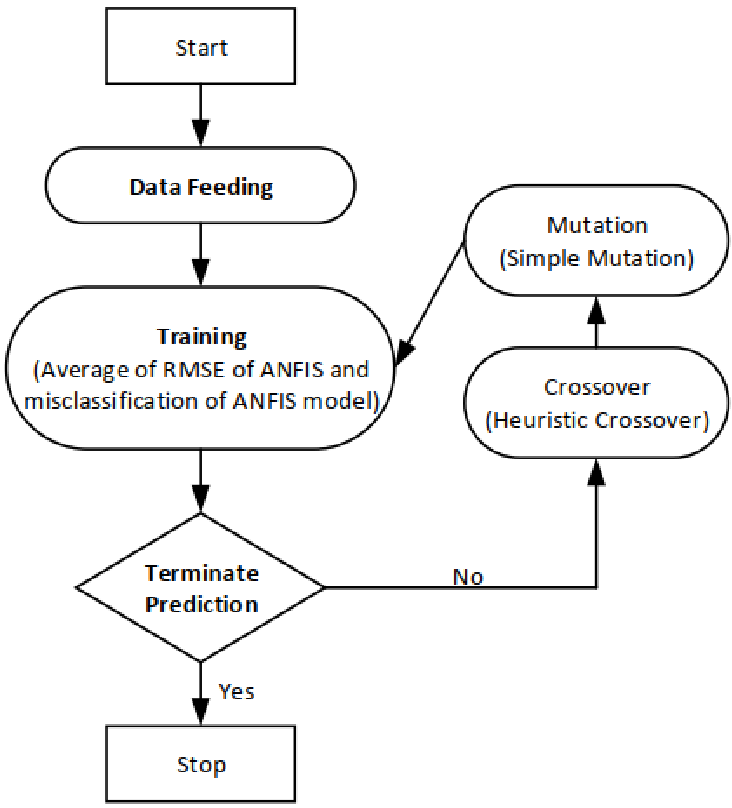

Figure 4-4 Optimized ANFIS model with Genetic Algorithms (Ineza Havugimana et al., 2023)

The research showed that blends of biodiesel (B10 and B20) helped lower emissions of HC, CO, CO_2, and PM, although they led to a slight increase in NOx. The creation of distinct ANFIS models for each pollutant resulted in predictions for NOx and CO_2 that proved to be very dependable, showcasing the promise of neuro-fuzzy models in enhancing fuel efficiency and reducing emissions in marine propulsion systems.

In another research, Wu et al. (2021) proposed a framework that used deep reinforcement learning to manage energy in hybrid-electric marine propulsion systems. The research utilized a Twin-Delayed Deep Deterministic Policy Gradient (TD3) agent, which was trained on historical load profile data, to create an energy management strategy that can simultaneously control multiple power sources. This AI-driven method when applied to a coastal ferry model, outfitted with batteries and fuel cells, reached near-optimal performance in cutting emission and fuel use.

4.3 AI in Fault Detection and Diagnosis

Implementing Artificial Intelligence (AI) into fault detections and diagnosis systems has greatly improved the reliability and safety of marine engine controls. As marine diesel engines run under high temperatures and pressure, they are vulnerable to a variety of faults that can risk the operation of vessels. Traditional diagnostics method like oil analysis and vibration monitoring often lacks real-time accuracy in fault detections because they depend on manual interpretations and are affected by environmental noise. AI-driven methods tackle these limitations by providing automated, precise, and efficient solution for faults diagnosis.

The research carried out by Mendonça et al. (2024) indicates that model-based residual analysis is employed for fault detections and diagnosis (FDD) in marine engine control involving a mathematical model that predicts the normal behavior of the systems. These estimates are continuously compared with real-time sensors data, and discrepancies called residuals indicate potential faults. Thresholds helps in identifying whether a fault is present and how serious it could be. AI-driven procedure refines this process by utilizing deep learning and neural network so that it can evaluate large datasets, recognize complex pattern, and adapt in different conditions. Figure 4.5 illustrates how this proposed approach looks like.

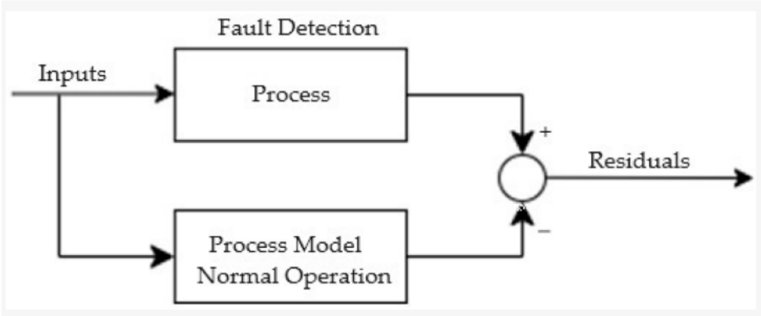

Figure 4-5 Fault detection approach (Residual analysis-based) (Mendonça et al., 2024)

By integrating data-driven concept with physics-based models, hybrid approaches improve the accuracy of fault detections. The integration of AI enhances the efficiency of real-time diagnostic and minimizes the need for manual interventions. By using historical fault data to predict failures, proactive maintenance schedules can be achieved and engine downtime minimized through predictive maintenance approaches. AI-based FDD is a crucial component of modern marine engine control system as it enhances operational performances and prolong engine lifespans.

A significant application of AI is employing deep learning models to analyze engine parameters and research has been done by Chen et al. (2024) presented a model called Multi-Scale Attention Transformer (MSAT) that is design for handling intricate engine pressure signals. By utilizing both low-resolutions and high-resolution attention mechanism this model captures multi-scale features that facilitate the detections of subtle fault characteristic. The experimental findings showed that the MSAT model achieved a classification accuracy of more than 99% in conditions with a high signal-to-noise ratios and it maintained an accuracy of over 95% even amid considerable noise interferences. This type of results underscores its robustness for real-time monitoring.

Another AI method uses neural network algorithms to diagnose multiple simultaneous faults in marine diesel engines. While comparing different neural network model, it has been found that the Levenberg-Marquardt backpropagation neural networks reached diagnostic accuracy of 88.89% for multiple faults and 100% for single fault along with a diagnosis time of just 0.78 second (Zhu et al., 2023). Furthermore, Mendonça et al. (2024) suggested an intelligent fuzzy framework in their study aimed at improving faults diagnosis in maritime equipment. This methodology combines intelligent decision-making with model-based strategies using fuzzy modeling to forecast system outputs based on process input and outputs. The system produces residual that underscore inconsistencies suggestive of fault by comparing actual measurements with these forecasts. This organized approach enables effective identifications and isolation of faults strengthening the dependability of marine system. This framework has been deployed to a marine pneumatic servo-actuated valve that successfully identified and isolated three critical faults in its operation. These highlights the capability of AI to manage the complexities linked to engine faults which are difficult for conventional technique to diagnose with precisions.

4.4 Case Studies of AI Implementation in Marine Control Systems

Marine control system has seen a growing integration of Artificial Intelligence (AI), which has improved operational efficiency, safety, and sustainability. Below are few cases studies showing effective uses of AI in this field:

DNV GL's Veracity Platform: Predictive Maintenance

The Veracity platform created by DNV GL (a prominent maritime classifications society) employs AI for predictive maintenance and risk managements. The platform gathers and examine data from ship systems such as engine, pumps, and navigation equipment. It forecast equipment failures using machine learning models and suggests maintenance measures based on that. By taking this proactive approach, ship operators can ensure vessel safety and reliability, while reducing operational disruptions (Durlik et al., 2024).

ABB Ability™ Marine Pilot Control: Enhancing Vessel Maneuverability

The Marine Pilot Control system from ABB utilizes AI to enhance both the safety and maneuverability of vessel. Using AI-based models to forecast future vessel action based on gathered data, the system integrates essential vessel controls into one operator interfaces. With this predictive capability, key operations such as position-keeping, speed controls, braking assistance, and dockings can be automated. This enhances operational efficiency and reduces the possibility of human errors (ABB, 2024).

Wärtsilä's SmartPredict System: Enhanced Maneuvering

Wärtsilä, global leader in smart technologies for marine market, has created the SmartPredict system that employs AI to improve maritime safety and operational efficiency. SmartPredict aids in navigating ships by offering predictive insights derived from real-time data. To forecast future location and possible paths, the system examines data from the ship's sensors—such as its speed, directions, and environmental factors. This helps operators make well-informed choices to prevent collisions and groundings, thus enhancing safety during crucial maneuvers (Durlik et al., 2024).

Sea Machines Robotics: Autonomous Navigation

Sea Machines Robotics focuses on autonomous navigation and control systems for marine applications. The company wrapped up a major initiative called "The Machine Odyssey" in October 2021. With the Sea Machines SM300 system on board, a tugboat made an autonomous journey of more than 1,000 nautical miles around the Danish islands and through the Kiel Canal to Hamburg in Germany. The vessel was controlled remotely by operators in Boston, USA, more than 3,000 miles away. This demonstration exhibited how AI-powered autonomous navigation could reduce the need for an onboard crew and improve operational efficiency (Sea Machines, 2023)

Buffalo Automation: Autonomous Ferries

The development of self-driving water taxis and ferries has been initiated by Buffalo Automation. Europe's first commercial robotaxi service launched in July 2021 when an autonomous ferry started operating in the Kagerplassen Lake District of the Netherlands. The self-driving ferry employs AI to assess its environment and navigate autonomously, offering a sustainable transport alternative and reducing congestion on current access routes. Using a ridesharing app created by Buffalo Automation, passengers can hop on the ferry (Payne, 2021).

ABB Dynafin™ Propulsion Concept: Revolutionizing Marine Propulsion

Inspired by the movement of a whale's tail, ABB Marine & Ports collaborated with VTT to develop the Dynafin™ propulsion concept. With individually controlled vertical blades driven by permanent magnet motors, this cutting-edge system allows for precise adjustment of both the magnitude and direction of thrust. Because of this AI-driven control strategy, optimal blade trajectories are ensured, which leads to fuel consumption reductions of as much as 22% and significantly enhanced maneuverability in comparison with traditional screw propellers (ABB, 2023).

5 Conclusion and Future Outlook

5.1 Summary of Key Findings

This chapter outlines the core result of the study on AI-based control systems for marine engine. The study investigated traditional methods for controlling marine engines, the difficulties these methods encounter, and the ways in which artificial intelligence (AI) provides innovative solution for performance optimizations, predictive maintenance enhancement, and fuel efficiency improvements. The results include the knowledge achieved from earlier chapters and underscore the effect of AI integration into marine engine management.

1. Challenges in Traditional Marine Engine Control

Traditional marine engine control systems are predominantly based on rule-based and model-based methods and these traditional approaches often find it difficult to deal with uncertainties, nonlinearities, and dynamic environmental conditions (Carpanzano, 2023). Mechanical damages, delayed identification of faults and improper fuel use limits the efficiency of conventional control methods even more. The study indicates that these challenges require sophisticated control strategies to enhance the performances and reliability of marine engines.

2. AI as a Transformative Solution in Marine Engine Control

Technologies such as machine learning, fuzzy logic, and neural network that are driven by AI offer substantial enhancements compared to traditional control methods (Antonić & Komar, 2007). Real-time decision-making can be increased by using AI, as it allows marine engines to adapt in dynamic conditions. The study emphasizes that AI-based systems can handle extensive amounts of sensor data that can enable predictive maintenance and fuel optimizations.

3. Predictive Maintenance and Fault Detection

One of the most common uses of AI in marine engine control could be seen in predictive maintenance. AI models examine sensor data to anticipate component failures prior to their occurrences, which then reduces both downtime and maintenance expenses (Alamoush et al., 2024). This proactive approach helps in increasing operational efficiency and engine lifespans. The study highlights that safety is enhanced by AI-driven faults detection systems which detect anomalies in engine performances at an early stage and plan maintenance based on that.

4. AI-Based Fuel Efficiency and Emission Control

In marine engineering, fuel consumptions, and emissions are crucial issues. Control systems based on AI utilize real-time information to optimize fuel injections, modify engine parameter and lower emissions while maintaining performance standard (Alshareef & Alghanmi, 2024). The result indicate that methods based on AI can reduce greenhouse gas emission to a significant degree which is in accordance with global sustainability objectives and regulatory compliance.

5. Comparative Analysis: Traditional vs. AI-Based Systems

It has been shown through comparative analysis that AI-based systems outperform traditional methods especially in adaptability, efficiency, and fault resilience (Gao et al., 2023). Unlike traditional systems that depend on pre-established models, AI-driven systems learn from historical data that makes it possible to optimize the system continuously. However, the research acknowledges the difficulties related to implementing AI such as reliance on data, complex computations, and the necessity for qualified individuals to oversee AI-driven systems.

6. Case Studies of AI Implementation in Marine Control Systems

Many real-world case studies demonstrate how successful AI implementation has become in marine engine control systems. These examples indicate how the shipping industry and marine engineering professionals utilize AI to make the operations smooth, boost reliability, and lower operational expenses. The results indicate that the maritime sector is gradually embracing AI motivated by its prospects for long-term cost reduction and environmental advantages.

5.2 Challenges and Limitations of AI in Marine Engine Control

Artificial Intelligence (AI) has emerged as a revolutionary technology in marine engine control system providing benefits in predictive maintenance, fuel efficiency, and fault detection. However, despite its promising potential, the application of AI to marine engine management presents several challenges and limitations. This section analyzes the main obstacles to AI adoption and discusses the technical, operational, and regulatory issues related to AI-driven marine control system.

1. Data Dependency and Quality Issues

It is difficult to gather high-quality datasets which can be labeled as marine only, which is a critical issue for AI dependent marine engine control systems. These datasets are used to make decisions which are crucial to any vessel. AI model performances can be adversely affected by sensor inaccuracies, environmental changes, and the presence of missing or biased data. This may result in incorrect predictions and unreliable control action (Vu et al., 2024).

2. Computational Complexity and Real-Time Processing Constraints

Marine engine control demands real-time decision-makings but AI algorithms like deep learning models, often require considerable computational resource. Marine vessels often have limited onboard processing capabilities that may not efficiently support complex AI models leading to the need for advanced hardware or cloud-based processing and this brings delay and connectivity challenges (Lisowski, 2021).

3. Lack of Transparency and Explainability

AI models, especially those based on deep learning, function as black boxes, which complicates engineers' ability to comprehend and explain their choices. This absence of explainability gives rise to worries in applications where safety is paramount. In these situations, human operators must confirm the validity of AI-generated decisions and minimize possible mistakes in marine engine control (Ucar et al., 2024).

4. Integration Challenges with Existing Control Systems

As many marine vessels still utilize traditional control mechanisms, it is difficult to incorporate AI-based solutions efficiently. Incorporating AI into legacy systems might require extensive changes to both software and hardware, which could raise costs and lead to increased downtime for fleet operators. Furthermore, guaranteeing that AI-driven systems are compatible with current maritime communication protocols continues to be a technical challenge (Aström & Murray, 2010).

5. Cybersecurity and Data Privacy Risks

With the digitalization of marine engine control, new vulnerabilities to cyberattacks arise. Because AI systems need constant data transfer among sensors, control units, and cloud servers, they can be targeted for hacking or data breaches. It is vital to establish strong cybersecurity frameworks and encryption mechanisms in order to safeguard AI-powered marine control systems against external threats (Tuomala, 2021).

6. High Implementation Costs and Skill Gaps

It takes a substantial investment in hardware-software and skilled personnel to develop and implement AI-based marine control solution. Many shipping companies might be reluctant to embrace AI because of the significant initial costs and the requirement for specialized knowledge in AI, data sciences, and marine engineering. Training marine professionals in the operation, interpretations, and maintenance of AI systems increases both the costs and complexities associated with AI's adoption (Grech et al., 2019).

Although AI offers great promise for transforming marine engine control, several challenges and limitations need to be tackled to guarantee its effective implementations. Data quality, computational constraints, integration issues, cybersecurity risk, regulatory compliances and cost factors are all crucial in successful AI adoption in the maritime industry.

5.3 Future Trends: Autonomous Marine Systems and AI Integration

Automation technology and artificial technology (AI) in marine industry are bringing a significant transformation. This chapter evaluate both developing trends of AI integration into autonomous marine system as well as the possible challenges and prospects in this rapid growing area.

A) The Rise of Autonomous Marine Systems

Autonomous marine systems refer to vessels and platform that can function with minimal or no human involvements, which can utilize AI, machine learnings (ML), computer vision and sensor fusion technologies to perform various functions like navigation, collision avoidances, and making operational decisions. The International Maritime Organization (IMO) and classification societies are actively working in developing regulatory frameworks to guarantee the safe introduction of autonomous vessels (Alamoush et al., 2024).

Autonomous vessels are categorized into various levels according to the magnitude of human involvement:

1. Remote-controlled ships with crew onboard: These vessels are generally navigated by human crews but utilize AI for assistances in various dynamic conditions.

2. Remote-controlled ships without crew onboard: These types of vessels operated from an onshore facility using AI for real-time decision-makings and control of the system.

3. Fully autonomous ships: There will be no crews onboard at all, as these vessels function independently using AI and automated control mechanisms requiring little human supervision or no supervision at all.

B) AI Integration in Autonomous Marine Systems

Three main domains could be characterized in the incorporation of AI into autonomous marine systems: perceptions and situational awareness, autonomous navigation and decision-makings, and predictive maintenance and condition monitoring.

1. Perception and situational awareness: Autonomous vessels can use AI-driven computer vision and LiDAR technologies to perceive their environments and identify obstacles to categorize marine object. These systems improve safety and operational efficiency by processing data from radar, sonars and cameras (Thombre et al., 2022).

2. Autonomous Navigation and Decision-Makings: Deep reinforcement learning and predictive analytics could help in a way that vessels can optimize their routes, avoid collisions and adjust to changing sea conditions in real time scenarios (Thombre et al., 2022).

3. Predictive Maintenance and Condition Monitoring: Engine performance data could be checked by machine learning models to foresee failure and arrange maintenance proactively to minimize downtimes and operational expense (Lundh, 2010).

C) Challenges and Future Considerations

Even with considerable advancements, yet autonomous marine systems encounter a number of challenges:

1. Regulatory and Legal Uncertainty: The maritime industry needs international regulations to tackle issue related to liability, cybersecurity, and operational safety.

2. Reliability and Redundancy: Reliability and redundancy need to be achieved by showing a high level of dependability particularly in severe weathers, so that AI systems could be adopted across the marine industry.

3. Cybersecurity Risks: Unauthorized access and manipulation of systems must be regulated by creating strong security frameworks for autonomous vessels, as they are more vulnerable to cyber threats.

With future developments in edge computing, digital twins and AI-driven fleet management system the capabilities of autonomous marine vessels will be further enhanced, leading to safer and more efficient maritime operations.

5.4 Recommendations for Future Research and Industry Adoption

There are numerous possibilities for improvements, efficiency and sustainability in the field of marine engine control systems with the inclusion of AI. Future studies should aim in way that it can improve real-time control systems and predictive accuracy by using hybrid AI models like combining neural network, fuzzy logics, and reinforcement learnings (Durlik et al., 2024). Moreover, trust and transparency both are crucial in AI-driven marine operations, and to do that AI-based decisions should be explainable and interpretable in an easy manner (Simion et al., 2024). Furthermore, AI-driven energy optimization techniques should be able to contribute to eco-friendly shipping by adjusting engine parameters dynamically according to operational and environmental conditions. Since AI-powered marine systems are becoming more vulnerable to cyber threats, this is another crucial potential sector to be investigated.

Pilot initiatives should be taken to encourage industry acceptance, and stakeholders should focus more in confirming the reliability of AI model in practical marine scenarios prior to their complete implementation. Standardized regulatory frameworks from organizations such as IMO are also important as it guarantees adherence of safety regulations. Furthermore, skill gaps should be minimized by prioritizing workforce training in AI technologies and establish competency center within maritime institutions. Digital twins could also be a potential solution to make it more marine industry friendly for AI-driven simulations, as it can augment predictive analytics and decision-makings prior to real-world implementation. Working with aerospace and automotive sectors could speed up AI advancements in marine sector as well and focus should be on that too. With adherence to these recommendations AI can be effectively utilized by the maritime industry to improve marine engine control, optimize fuel efficiency, and promote sustainable shipping practices (ABB, 2024).

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