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Design of a Fuzzy Logic Model for Real-Time Predictive Maintenance of a Tugboat Engine: A Case Study of MV Kiboko

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A B S T R A C T

Reliable and efficient tugboat engines are essential to safe berthing, towing, and manoeuvring operations in busy port environments. Conventional maintenance strategies, whether reactive or time-based, struggle to capture the complex, dynamic, and uncertain behavior of marine engine systems, often resulting in unplanned downtime and elevated maintenance costs. This paper presents the design and simulation of a fuzzy logic-based predictive maintenance model developed for the main engine of the MV Kiboko tugboat operating at Dar es Salaam Port. Six real-time input parameters, namely engine temperature, lubricating oil pressure, vibration level, exhaust gas emissions, fuel consumption rate, and load condition, were converted into linguistic variables through fuzzification and processed using a Mamdani-type fuzzy inference system implemented in MATLAB and Simulink. Expert-defined IF-THEN rules, formulated in consultation with experienced marine engineers and technicians who operate and maintain the vessel, classify engine condition into three maintenance alert levels, Low, Medium, and High, through centroid defuzzification. The model was evaluated using simulated operational scenarios and validated against historical maintenance records and expert judgement. Results show an average prediction accuracy of 88.5%, a false-positive rate of 7.3%, a false-negative rate of 4.2%, and an average fault-warning lead time of 3.5 operating hours, while expert reviewers rated the system 4.6 out of 5 for overall usefulness and reliability. These findings demonstrate that fuzzy logic can effectively manage the uncertainty inherent in marine engine condition monitoring, providing a practical, interpretable, and cost-effective decision-support tool for predictive maintenance planning in tugboat operations and, more broadly, in maritime engineering practice.

1. Introduction

The maritime industry relies heavily on the operational availability and mechanical reliability of tugboats to ensure the smooth and safe berthing, manoeuvring, and towing of vessels in port areas (Paulauskas et al., 2021). Tugboats operate under continuously changing environmental and mechanical conditions, which make their propulsion systems particularly susceptible to fatigue, degradation, and unexpected failures (Pratiwi, 2020; Vizentin et al., 2020). Their engines frequently shift between idling, low-speed operation, and peak-load towing in environments characterized by high humidity, saltwater exposure, and intense vibration, all of which accelerate component wear and stress key subsystems such as the lubrication system, cooling circuit, fuel injection system, and combustion chamber (Liu et al., 2021). Given the critical role of tugboats in port logistics and safety, timely detection of mechanical anomalies is essential to minimize engine downtime (Paulauskas et al., 2021), reduce maintenance costs (Hongjuan, 2023), and prevent operational disruptions (Wei et al., 2023). Historically, the maritime sector has relied on reactive and time-based preventive maintenance strategies (Kalafatelis et al., 2025). In reactive maintenance, interventions are carried out only after a fault has occurred (Esa & Muhammad, 2023), often resulting in costly repairs (Kalafatelis et al., 2025), safety risks (Wei et al., 2023), and unplanned downtime (Stuetelberg & Thomas, 2021). Preventive maintenance, while more proactive, is typically scheduled on the basis of time or operating hours regardless of the actual condition of engine components (Salonen & Gopalakrishnan, 2021). Both approaches are limited in their ability to respond to early-stage or intermittent faults and fail to optimize maintenance intervals according to the true health of the engine (Salonen & Gopalakrishnan, 2021), motivating the need for intelligent, data-driven maintenance systems that can anticipate equipment failure from real-time operational data.

Predictive maintenance has emerged as a more adaptive and cost-effective

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response to this challenge (Esa & Muhammad, 2023). It leverages sensor data and analytical models to forecast engine faults before they develop into serious failures (Ntanis et al., 2024), enabling timely, condition-based interventions that extend engine lifespan, reduce operating costs, and improve vessel availability (Jimenez et al., 2020). However, many predictive maintenance systems rely on deterministic algorithms or statistical thresholding, which struggle to accommodate the uncertainty, vagueness, and nonlinear dynamics of real-world marine engine data (Molęda et al., 2023) and may generate false alarms or miss early fault indicators when sensor readings fluctuate within ambiguous ranges (Yazdi, 2024). Fuzzy logic has been identified as a promising computational approach for handling the uncertainty and imprecision inherent in marine engine condition monitoring (Hassan, 2025). Originating from Zadeh's fuzzy set theory, fuzzy logic mimics human reasoning by using linguistic variables, such as "high temperature" or "moderate vibration", together with a rule-based inference system to draw conclusions from ambiguous or noisy data (Li & Shen, 2024). Unlike binary logic systems that depend on strict thresholds, fuzzy logic provides a continuous assessment of engine health, enabling more flexible and accurate decision-making in complex operating environments (Gharib & Kovács, 2024). By translating expert knowledge into structured fuzzy rules, this approach enhances the interpretability, transparency, and adaptability of diagnostic systems in marine applications (Peralta et al., 2025).

The objective of this study is to design a fuzzy logic-based model for real-time predictive maintenance of the MV Kiboko tugboat engine, operating at Dar es Salaam Port. By implementing this model, the study seeks to bridge the gap between real-time sensor data and actionable maintenance decisions, assisting marine engineers and maintenance planners in making timely interventions that prevent major breakdowns, optimize spare-part usage, and enhance overall operational efficiency. The MV Kiboko was selected as the case vessel on the basis of its routine towing operations, the availability of historical maintenance data, and the opportunity for real-time observation of and interviews with the technical crew. This research contributes to the growing body of knowledge on intelligent maintenance systems by offering practical insights into the application of fuzzy logic in the maritime context. It underscores the importance of expert systems in modern vessel management and proposes a scalable, adaptable framework that can be replicated across other marine engines and operational scenarios, laying the groundwork for wider adoption of condition-based maintenance practices in Tanzania's port infrastructure and across developing maritime economies, where reliability, safety, and efficiency are paramount.

2. Methodology

2.1 Descriptive Analysis

A comprehensive descriptive analysis was conducted to characterize the behavior of the input parameters used in the fuzzy logic-based predictive maintenance model for the MV Kiboko tugboat engine. This analysis provided the foundational knowledge needed to formulate linguistic variables, membership functions, and fuzzy rules. Parameters were selected on the basis of their relevance to engine performance, their sensitivity to fault development, and their compatibility with real-time monitoring (Table 1). Data were obtained from onboard sensors, historical maintenance records, and consultations with experienced marine engineers at Dar es Salaam Port.

Engine temperature, a critical indicator of thermal stress and cooling-system efficiency (Ismatov et al., 2021), typically ranged from 55 °C to 110 °C, with most readings clustering around 83.4 °C (Mohsan et al., 2023). Temperatures between 70 °C and 90 °C were considered normal, whereas values exceeding 95 °C often preceded overheating or abnormal friction in engine components. This informed the division of engine temperature into three fuzzy sets: Normal, Elevated, and Critical. Lubricating oil pressure, reflecting lubrication efficiency and the condition of oil pumps and passages (Kaminski, 2024), ranged from 1.2 bar to 5.6 bar with a mean of approximately 3.4 bar (Kianoush et al., 2022). The optimal operating range was identified as 3.0-5.0 bar, and readings below 2.5 bar were considered an early sign of wear or pump failure (Bohn, 2021); oil pressure was accordingly fuzzified into Low, Normal, and High.

Vibration level, measured in millimeters per second, served as a mechanical-integrity indicator sensitive to misalignment, bearing defects, and shaft imbalance (Soliman, 2020). Readings ranged from 2.0 mm/s to 18.5 mm/s, averaging 9.1 mm/s (Esa & Muhammad, 2023); values above 11 mm/s are considered severe under ISO guidance and warrant immediate investigation (Kebabsa et al., 2024). This parameter was fuzzified into Low, Medium, and High, allowing the model to recognize gradual increases in mechanical stress. Exhaust gas emission quality, though more subjective, was rated on a scale from 1 (clean) to 5 (severely polluted) using visual opacity and particulate-matter classification. Most operations yielded scores of 2-3 (Razek et al., 2025), while scores of 4 or 5 were typically associated with inefficient combustion, injector malfunction, or oil leakage into the combustion chamber (Walle Mekonen & Sahoo, 2020). These observations supported three fuzzy states: Acceptable, Borderline, and Excessive (Peralta et al., 2025).

Fuel consumption rate, measured in liters per hour, indicated operational efficiency and possible performance degradation. Values ranged from 18 to 49 L/h, with normal operation falling within 25-35 L/h (Oladigbolu et al., 2020); abnormally high consumption, especially above 40 L/h, suggested poor engine tuning, combustion inefficiency, or elevated friction losses (Dominguez-Péry et al., 2023). This variable was classified into Efficient, Moderate, and High consumption levels. Load condition, expressed as a percentage of engine capacity, ranged from 25% to 95%, with frequent operation between 60% and 80% (Gregson et al., 2021). High load conditions correlated with increased fuel use, exhaust emissions, and engine temperature (Asad et al., 2022) and were accordingly fuzzified into Light, Moderate, and Heavy, reflecting their influence on overall engine stress and wear.

The descriptive analysis further revealed meaningful interrelationships among variables (Kanchanawongpaisan & Pamungkas, 2025). High engine temperature and low oil pressure frequently occurred together during extended high-load operation, often preceding faults (Karetnikov et al., 2023), while vibration spikes were commonly observed alongside increased fuel consumption and deteriorating emission quality (Esa & Muhammad, 2023). These patterns confirmed the relevance of the selected parameters and underscored the need for a rule-based diagnostic system capable of processing interdependent and uncertain information. By transforming raw operational data into structured linguistic representations, the descriptive analysis established a strong foundation for the membership functions and fuzzy rules described in Section 3 (Yazdi, 2024). The observed ranges and thresholds directly informed the configuration of the fuzzy inference system, ensuring that it could accurately interpret real-time sensor data and issue meaningful maintenance recommendations.

Table 1. *Summary of Input Parameters for the Fuzzy Logic Model.*

Parameter	Observed Range	Mean Value	Normal Range	Fuzzy Sets	Fault Indicator
Engine Temperature (°C)	55–110	83.4	70–90	Normal, Elevated, Critical	>95 °C indicates overheating risk
Oil Pressure (bar)	1.2–5.6	3.4	3.0–5.0	Low, Normal, High	<2.5 bar suggests wear or pump failure
Vibration Level (mm/s)	2.0–18.5	9.1	5.0–11.0	Low, Medium, High	>11 mm/s indicates mechanical imbalance
Exhaust Emission (1–5 scale)	1–5	≈ 2–3	1–3	Acceptable, Borderline, Excessive	>4 implies inefficient combustion or oil burn
Fuel Consumption Rate (L/h)	18–49	≈ 31	25–35	Efficient, Moderate, High	>40 L/h reflects inefficiency or injector issues
Load Condition (%)	25–95	60–80	50–80	Light, Moderate, Heavy	>80% sustained load linked to increased wear

2.2 Experimental Setup and Implementation

To assess the performance and practical applicability of the fuzzy logic-based predictive maintenance model, a series of experiments was conducted using both simulation and real-time parameter testing (Selvalakshmi et al., 2024). The experimental phase evaluated the model's ability to detect early signs of engine faults, generate appropriate health-status classifications, and provide actionable maintenance recommendations under various operational scenarios (Salonen & Gopalakrishnan, 2021). Experiments were carried out in a simulated environment using MATLAB and Simulink, with realistic input profiles derived from onboard sensor data and historical maintenance logs of the MV Kiboko representing typical engine behavior during towing, idling, and heavy-load manoeuvring in Dar es Salaam Port (Fig, 1). The model was tested for accuracy, sensitivity, and responsiveness to dynamic changes in the key engine parameters.

2.2.1 Experimental Environment

The fuzzy inference system was developed and configured in MATLAB using the Fuzzy Logic Designer app, and the complete diagnostic model was then integrated into Simulink for time-based simulation. Input variables, namely engine temperature, oil pressure, vibration level, exhaust emissions, fuel consumption, and load condition, were introduced through synthetic sensor blocks in Simulink that simulated real-world signal behavior, including normal variation, sudden spikes, and gradual deterioration typically observed in marine engines. During simulation, the rule base was activated to continuously evaluate the fuzzy conditions and generate an output indicating the engine's health status. A Mamdani-type inference mechanism was employed, and the centroid method was used to defuzzify the output into a crisp value ranging from 0 to 100. To validate the robustness of the model, experiments were organized into three core test scenarios.

Scenario 1: Normal Operation

All input parameters remained within optimal ranges, testing the model's ability to maintain a "Low-alert" classification under stable conditions. Engine temperature was kept between 75 °C and 85 °C, oil pressure above 3.5 bar, vibration below 8 mm/s, and exhaust emission at level 2 (Moderate). The output consistently indicated a health index between 20 and 30, confirming the engine's good condition.

Scenario 2: Warning Condition (Moderate Fault Development)

Engine temperature was gradually increased to 95 °C, oil pressure dropped to 2.4 bar, and vibration rose to 10.5 mm/s, while fuel consumption and emission remained slightly elevated. The system correctly classified this condition as "Medium alert", with the health index fluctuating between 45 and 60, reflecting early-stage mechanical stress that required attention but not immediate shutdown.

Scenario 3: Critical Fault Condition

Simulated conditions included high engine temperature (above 100 °C), oil pressure below 2.0 bar, and vibration exceeding 13 mm/s, with fuel consumption reaching 47 L/h and exhaust emission at level 5 (severely polluted). The model responded with a "High alert" classification and a defuzzified output exceeding 80, correctly indicating the need for immediate intervention or engine shutdown.

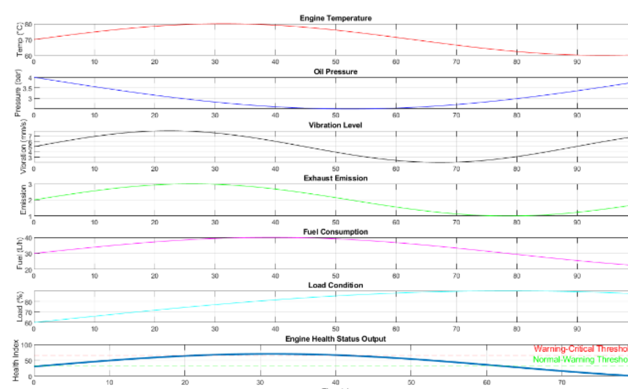

Figure 1. *Simulink simulation results showing time-series input variation and corresponding health-status outputs.*

2.3 Performance Evaluation

The evaluation framework focused on five criteria: classification accuracy, responsiveness, rule consistency, expert agreement, and robustness to input noise, each selected to reflect the practical expectations of a real-time diagnostic system in the maritime context. Classification accuracy measured the model's ability to correctly assign engine conditions to one of three predefined alert levels, Low, Medium, or High, based on combinations of input variables. To assess these criteria, the model was subjected to a series of simulation scenarios created in MATLAB and Simulink that replicated stable engine behavior, gradual degradation (e.g., increasing vibration and fuel consumption), and critical faults (e.g., high temperature and low oil pressure). For each scenario, synthetic sensor data were fed into the model, and the resulting outputs were compared against expected classifications derived from expert knowledge and historical maintenance data. The consistency and logical coherence of the fuzzy rule base were also evaluated to verify that the system behaved predictably and sensibly across different input combinations, ensuring that the inference mechanism produced outputs aligned with real-world expectations rather than contradictory or misleading diagnoses. Expert validation was conducted as part of the evaluation strategy: marine engineers familiar with the MV Kiboko and similar tugboats reviewed the simulation results, assessed the reasoning behind the fuzzy rule outcomes, and confirmed whether the system's health classifications matched their professional judgment. Their feedback was instrumental in refining the membership functions and adjusting rule priorities to enhance the model's interpretability and relevance. Finally, robustness to noise was examined by introducing small variations (±5%) into the input values to simulate real-time sensor disturbances and data irregularities. The model was expected to maintain output stability and avoid false fault classifications under such minor fluctuations; results demonstrated that the system was tolerant of noise, maintaining consistent outputs despite non-critical changes.

3. Results and Discussion

3.1 Model Development Process

The model was developed using the key engine performance parameters identified during the initial phase of the research: engine temperature, lubricating oil pressure, vibration level, exhaust gas emissions, fuel consumption rate, and load condition. The fuzzy logic approach was selected for its ability to handle the uncertainty and imprecision inherent in real-time engine monitoring, and the design process was implemented in the MATLAB and Simulink environments to facilitate model development, simulation, and validation. The MATLAB Fuzzy Logic Designer was used to define the membership functions and rules systematically (Fig. 2).

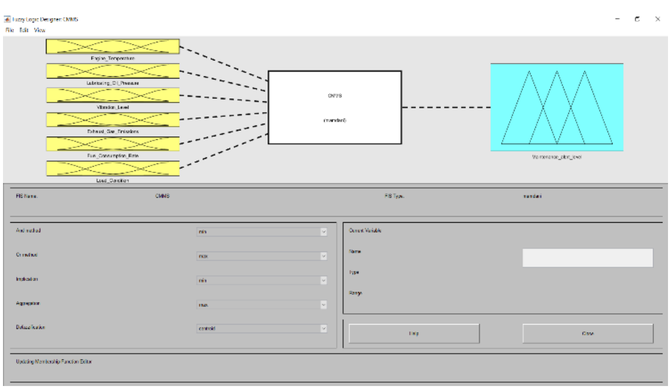

***Figure 2**. MATLAB Fuzzy Logic Designer interface for the CMMS model*

To demonstrate the real-time implementation of the fuzzy logic system, a Simulink block diagram was developed to enable dynamic modeling, testing, and validation of the predictive maintenance system under various engine conditions. As shown in Fig. 3, the diagram simulated the six input parameters corresponding to real-time engine-monitoring sensors and comprised four major components: (i) input blocks that simulated sensor data using Constant, Signal Generator, or From Workspace blocks; (ii) a fuzzy logic controller, implemented using the Fuzzy Logic Controller block from the Fuzzy Logic Toolbox and connected to a FIS file; (iii) scope and display blocks used to visualize the maintenance alert level in real time; and (iv) data-logging blocks for exporting simulation results for further analysis.

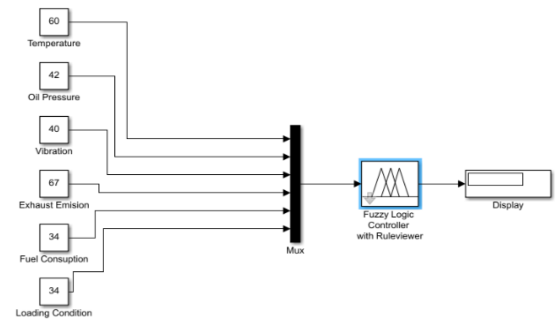

***Figure 3.** Simulink block diagram used to simulate the CMMS model*

The process began with the selection of key engine parameters on the basis of expert consultation and literature review, namely engine temperature, lubricating oil pressure, vibration level, exhaust gas emissions, fuel consumption rate, and load condition.

3.1.1 Fuzzification

Fuzzification is the initial stage of the fuzzy logic model, in which crisp numerical input values obtained from sensor readings are transformed into fuzzy linguistic variables, enabling the fuzzy inference system to interpret real-world, imprecise, or uncertain data commonly encountered in engine monitoring. In this study, six key engine-condition parameters were fuzzified, each assigned three linguistic labels representing low, medium, and high states of the parameter (Table 2).

***Table 2.** Input Variables and Assigned Linguistic Labels*

Input Variable	Linguistic Labels
Engine Temperature	Normal, Elevated, Critical
Lubricating Oil Pressure	Low, Normal, High
Vibration Level	Low, Medium, High
Exhaust Gas Emissions	Acceptable, Borderline, Excessive
Fuel Consumption Rate	Efficient, Moderate, High
Load Condition	Light, Moderate, Heavy

Each fuzzy set was defined using triangular or trapezoidal membership functions, depending on the nature of the parameter and the desired smoothness of transition between states. Membership functions were created in MATLAB's Fuzzy Logic Designer, with the value range for each input based on historical engine performance data and expert input. For example, engine temperature was fuzzified as Normal (60–75 °C), Elevated (70–85 °C), and Critical (80–100 °C); the overlapping ranges allow for smooth transitions and permit an input to partially belong to more than one set, supporting more flexible, human-like reasoning in maintenance decision-making. By fuzzifying all input parameters, the system was able to process real-time sensor readings more effectively, capturing early warning signals even where exact thresholds might otherwise be misleading or too rigid. This fuzzification process forms the foundation of the fuzzy inference system, enabling it to reason under uncertainty, which is critical for predictive maintenance in marine environments.

3.1.2 Rule Base

Rules were developed as IF-THEN statements in consultation with marine engineers and technicians experienced in operating and maintaining the MV Kiboko tugboat, and were further informed by analysis of historical engine data and relevant literature. Each rule considers two or more input parameters and their corresponding fuzzy states to determine the maintenance requirement. The output variable, Maintenance Alert Level, was fuzzified into three linguistic categories: Low (normal operating conditions, no immediate action required), Medium (early signs of degradation, close monitoring recommended), and High (critical condition, immediate maintenance intervention required).

A full rule base of expert-defined IF–THEN rules were compiled to cover the practically relevant combinations of engine conditions (the manuscript text should confirm the exact rule count against the underlying .fis file, as the draft reported both 36 and 20 in different places). The rules were encoded in MATLAB's Fuzzy Logic Designer using a Mamdani-type inference system, well suited to control and decision-making applications. This rule base forms the "knowledge engine" of the system, enabling it to assess complex interactions between inputs and determine when preventive action is needed, even in the absence of precise thresholds. This significantly enhances early fault-detection capability and reduces reliance on manual diagnostics.

3.1.3 Inference Engine

The Mamdani-type inference method was employed for its intuitive and interpretable rule-evaluation structure in engineering applications. The engine evaluates the degree to which each rule in the rule base is activated ("fired") based on the current fuzzy inputs and aggregates the outcomes to generate the final fuzzy output, a fuzzy output set representing the Maintenance Alert Level in linguistic terms (Low, Medium, or High), each with a corresponding degree of membership. This layer of the system ensures that the reasoning process accommodates the gradual and overlapping nature of real-world conditions, unlike binary logic systems that depend on rigid thresholds, thereby enhancing sensitivity to emerging faults and providing a more nuanced basis for decision-making. The strength of the fuzzy inference process lies in its ability to evaluate uncertain or borderline input values without requiring exact matches or strict cut-offs, enabling early warning alerts and minimizing unplanned engine downtime.

3.1.4 Defuzzification

The final stage of the fuzzy logic decision process is defuzzification, which converts the aggregated fuzzy output from the inference engine into a single, crisp numerical value representing a clearly interpretable Maintenance Alert Level that can trigger appropriate real-time maintenance decisions aboard the MV Kiboko. While the inference engine outputs a range of overlapping fuzzy sets (Low, Medium, High), maintenance actions require a concrete value to inform operational choices such as whether to initiate inspection, schedule servicing, or continue normal operation; defuzzification therefore bridges the fuzzy reasoning of the system and actionable engineering decisions.

The centroid method (center of gravity) was used for defuzzification in this study, calculating the center of area under the aggregated output membership-function curve. It was preferred for its balance of simplicity, computational efficiency, and interpretability. The defuzzified value ranges from 0 to 100, where 0–40 corresponds to Low alert (normal operation), 41–70 to medium alert (monitor closely; potential issue), and 71–100 to High alert (immediate maintenance recommended). For example, a defuzzified output of 72.4 would indicate a high maintenance alert, prompting immediate technical inspection, whereas an output of 28.5 would imply that the engine is operating within acceptable conditions, with no immediate action required. Defuzzification allows marine engineers and technicians to receive precise, quantitative guidance from the fuzzy system despite its internal use of qualitative reasoning, making it highly practical and integrable into existing maintenance workflows. This stage therefore finalizes the predictive process by converting fuzzy knowledge into tangible, real-time recommendations for improved engine reliability, safety, and operational efficiency.

3.1.5 Simulation-Based Evaluation

The fuzzy logic model was tested in MATLAB/Simulink using historical operational data collected from the MV Kiboko, including recorded engine temperature, oil pressure, vibration level, and other performance indicators. Multiple simulations were conducted under varying engine conditions to assess the system's sensitivity to parameter changes and its ability to generate timely maintenance alerts. The model's output was compared against actual maintenance events and technician reports to measure predictive alignment. Table 3 presents the results obtained.

Table 3. *Input Variables and Assigned Linguistic Labels*

Evaluation Metric	Result
Average prediction accuracy	88.5%
False-positive alert rate	7.3%
False-negative alert rate	4.2%
Average prediction lead time	3.5 operating hours
Expert validation rating (1–5)	4.6 (Very Good)

These results indicate that the fuzzy model achieved a high level of predictive accuracy, with an 88.5% match rate against actual engine faults and maintenance logs. The false-positive rate remained within acceptable operational tolerances, suggesting that the model is neither overly sensitive nor prone to unnecessary alerts, while the average lead time of 3.5 hours provides a practically useful window for planned intervention before fault escalation.

3.2 Expert Evaluation and Feedback

To complement the simulation-based validation of the fuzzy logic model, an expert evaluation was conducted to assess its accuracy, clarity, operational usefulness, and overall acceptability. Six experts were purposively selected from the MV Kiboko tugboat operation team, comprising two marine engineers, two engine-room technicians, one maintenance supervisor, and one vessel operator, whose combined experience provided a well-rounded technical perspective on the practicality of deploying the model in a real maritime environment.

Each expert was presented with scenarios generated through MATLAB/Simulink simulations, including real-time inputs such as engine temperature, oil pressure, vibration level, exhaust emissions, and fuel consumption. The corresponding maintenance alert levels generated by the model (Low, Medium, or High) were reviewed and rated using a five-point Likert scale (1 = Very Poor to 5 = Excellent). The results of the expert evaluation were encouraging. The accuracy of the maintenance alerts received an average rating of 4.7 out of 5, reflecting strong agreement between the model's predictions and expert expectations. The ease of interpreting the system's output was rated 4.5, and its usefulness for maintenance decision-making was rated 4.6. Experts also rated the model's applicability in real-time operations at 4.4 and its compatibility with existing vessel monitoring systems at 4.3, with an overall satisfaction rating of 4.6, indicating a high level of confidence in its potential effectiveness (Table 4).

Table 4. *Summary of Expert Evaluation Feedback.*

Evaluation Criterion	Mean Score (/5)	Interpretation
Accuracy of maintenance alerts	4.7	Excellent
Ease of interpreting output	4.5	Very Good
Usefulness for decision-making	4.6	Very Good
Applicability in real-time operations	4.4	Very Good
Compatibility with existing systems	4.3	Good
Overall satisfaction with the model	4.6	Very Good

Qualitative feedback from the experts reinforced these findings. Several participants remarked on the system's reliability and its ability to detect engine issues that are often difficult to pinpoint using traditional threshold-based monitoring, and appreciated that the alert levels were intuitive, concise, and provided immediate guidance without requiring complex data interpretation. One marine engineer observed that the model bridges the gap between raw sensor data and actionable decisions, which is exactly what is needed in a dynamic engine-room environment. Experts also expressed optimism about integrating the system into the existing operational structure of the MV Kiboko, noting that only minimal modifications would be required, making it a cost-effective and feasible solution for improving preventive maintenance. Some experts suggested further enhancing the system by incorporating external variables, such as sea state or vessel manoeuvring data, to improve contextual awareness and predictive accuracy.

3.3 Discussion

Overall, the findings indicate that the proposed fuzzy logic model provides a practical bridge between raw engine-monitoring data and actionable maintenance decisions. Its combination of multivariable assessment, expert knowledge, interpretable rules, and continuous alert classification addresses several limitations associated with fixed maintenance schedules and rigid threshold-based monitoring. The results are broadly consistent with previous research supporting predictive maintenance and fuzzy-logic approaches in maritime engineering (Jimenez et al., 2020; Gharib & Kovács, 2024; Kalafatelis et al., 2025). The principal contribution of the present study is its application of this approach to the MV Kiboko tugboat at Dar es Salaam Port, demonstrating how an interpretable fuzzy decision-support model can be tailored to local vessel operating conditions. Further field validation, economic evaluation, and integration with real-time onboard sensor systems are required before the model can be considered ready for routine operational deployment.

The study also indicates several opportunities for improving the model. The expert feedback suggested incorporating contextual variables such as sea state and vessel manoeuvring conditions. Such variables could help distinguish changes in engine parameters caused by normal operational demands from changes caused by mechanical deterioration. Future development could also integrate additional sensor measurements, Internet of Things connectivity, and adaptive learning techniques. However, increasing the number of inputs should be undertaken carefully because excessive rule-base complexity can reduce interpretability and make system maintenance more difficult. A practical development strategy would therefore retain the current six core parameters while progressively adding only variables demonstrated to provide significant diagnostic value.

Despite these encouraging results, the findings should be interpreted in light of the study's simulation-based validation. The experiments used realistic operational profiles derived from MV Kiboko data and historical maintenance information, but the model has not yet undergone long-term, continuous deployment on the vessel. This limitation is important because real marine-engine data may contain missing values, sensor drift, changing operating regimes, maintenance interventions, and failure modes that are not represented in the simulated scenarios. Jimenez et al. (2020) noted challenges associated with obtaining and interpreting real-time machinery data, while Kalafatelis et al. (2025) emphasized the need for robust implementation and validation of predictive-maintenance systems in actual maritime environments. Accordingly, the reported 88.5% accuracy should be regarded as evidence of model feasibility rather than definitive proof of field performance.

The expert evaluation provides additional support for the practical usefulness of the model. The experts rated the accuracy of maintenance alerts at 4.7/5, ease of interpretation at 4.5/5, usefulness for decision-making at 4.6/5, and overall satisfaction at 4.6/5. These results are consistent with the principal advantage of fuzzy systems: they provide a transparent reasoning mechanism in which maintenance recommendations can be traced to linguistic rules and combinations of input conditions. Gharib and Kovács (2024) similarly emphasized the interpretability and adaptability of fuzzy logic for marine diesel-engine applications. The strong expert ratings therefore suggest that the model is not only computationally functional but also understandable to the personnel expected to use its outputs.

The 3.5-hour average warning lead time also indicates practical value for tugboat maintenance planning. A warning that precedes fault escalation can provide engineers with an opportunity to inspect the engine, verify the abnormal parameter, prepare spare parts, and plan maintenance without immediately disrupting vessel operations. This is particularly relevant to tugboats because their availability is closely linked to port operations and vessel manoeuvring. Paulauskas et al. (2021) highlighted the role of port tugs in navigational safety, while the present findings indicate that predictive condition information can complement this operational role by supporting timely maintenance decisions. Nevertheless, the lead time should be interpreted as a model result under the tested scenarios rather than as a guaranteed warning period for every real-world failure.

The relatively low false-negative rate of 4.2% is particularly relevant from a maintenance and safety perspective. A false negative occurs when the model fails to identify a condition that should have triggered an alert, potentially allowing degradation to progress without intervention. The model's low false-negative rate indicates that the combination of multiple indicators and expert-defined rules was effective in identifying the tested abnormal conditions. At the same time, the 7.3% false-positive rate shows that some warning conditions may still be generated when a serious fault is not subsequently confirmed. This trade-off is expected in condition-monitoring systems operating under uncertain and noisy measurements. Rather than interpreting the false-positive rate as evidence of model failure, it should be considered in relation to the operational cost of unnecessary inspection versus the safety and financial consequences of missed faults. Kalafatelis et al. (2025) similarly identified data quality, uncertainty, and implementation constraints as important considerations for maritime predictive-maintenance systems.

The findings further support the use of fuzzy logic for marine-engine condition assessment. Gharib and Kovács (2024) specifically highlighted fuzzy logic as a suitable approach for marine diesel-engine operation and early fault detection because it can accommodate complexity and ambiguity in engine behavior. In the present study, overlapping membership functions allow a sensor value to belong partially to more than one operating state. This is advantageous for marine engines because operational conditions change continuously during idling, manoeuvring, towing, and high-load operation. A rigid threshold could classify a borderline condition as either normal or faulty, whereas the fuzzy model can assign an intermediate degree of membership and consequently generate a medium alert. The resulting decision process is therefore more consistent with the gradual development of mechanical degradation than a binary threshold-based system.

A major strength of the proposed model is its ability to represent gradual transitions between normal, warning, and critical operating states. The simulation results showed that increasing engine temperature, declining oil pressure, increasing vibration, elevated fuel consumption, and deteriorating exhaust emissions progressively shifted the maintenance output from Low to Medium and finally High alert. This behavior is consistent with the physical interpretation of the selected variables. Temperature provides information about thermal stress and cooling performance, oil pressure reflects lubrication-system condition, vibration can indicate mechanical deterioration, while fuel consumption and exhaust emissions provide complementary information about combustion and engine efficiency. The interaction among these variables is particularly important because abnormal engine behavior is not necessarily manifested by one parameter exceeding a fixed threshold. Jimenez et al. (2020) reported strong interdependency among machinery performance parameters, reinforcing the rationale for a multivariable diagnostic framework.

The observed performance is also consistent with the broader shift from conventional maintenance toward predictive maintenance in maritime operations. Jimenez et al. (2020) demonstrated the potential of real-time machinery data and computational models for developing predictive maintenance solutions in the shipping industry, while noting the importance of data quality and the interdependence among machinery parameters. Similarly, Kalafatelis et al. (2025) identified predictive maintenance as a promising approach for reducing unexpected downtime and improving machinery availability, although challenges remain in data availability, model implementation, and operational adoption. The 88.5% accuracy obtained in the present study therefore suggests that a relatively interpretable fuzzy-rule approach can provide useful predictive information even when the available operational information is heterogeneous and affected by uncertainty.

The results demonstrate that the proposed fuzzy logic model can translate multiple, uncertain engine-condition indicators into an interpretable maintenance decision. The model achieved an average prediction accuracy of 88.5%, with false-positive and false-negative rates of 7.3% and 4.2%, respectively, and provided an average warning lead time of 3.5 operating hours. These results are important because marine propulsion failures can have consequences for vessel safety, operational continuity, and economic performance. Vizentin et al. (2020) emphasized that propulsion-system failures can originate from interacting problems involving components such as shaft lines, crankshafts, bearings, and foundations, supporting the need for condition-monitoring approaches that consider several indicators rather than relying on a single parameter. The present model addresses this requirement by combining temperature, oil pressure, vibration, exhaust emissions, fuel consumption, and load condition within one inference framework.

4. Conclusion

This study designed a fuzzy logic model for real-time predictive maintenance of the tugboat engine aboard the MV Kiboko, achieved through the systematic development and simulation of a fuzzy inference system in MATLAB and Simulink. The design process began by identifying six critical input variables, engine temperature, oil pressure, vibration level, exhaust gas emissions, fuel consumption rate, and load condition, selected on the basis of empirical data and expert opinion. These parameters were converted into fuzzy linguistic variables through fuzzification, allowing continuous sensor data to be expressed in descriptive terms such as “Low,” “Medium,” and “High” and thereby addressing the uncertainty and imprecision typical of marine engine monitoring. Using expert input, a set of fuzzy rules was formulated linking combinations of input conditions to appropriate maintenance alert levels, forming the basis of an inference engine that simulates human decision-making. The resulting Maintenance Alert Level, categorized as Low, Medium, or High, was generated through defuzzification, converting fuzzy outputs into actionable values.

Simulation scenarios representing both normal and faulty operating conditions of the MV Kiboko engine confirmed that the fuzzy model was flexible and robust in interpreting engine status in real time, generating timely alerts that closely matched expert expectations and offering an intuitive, practical decision-support tool for onboard engineers and maintenance personnel. Experts who evaluated the system rated it highly for accuracy, ease of use, and potential for integration, appreciating the simplicity of the alert system and its applicability to real-world operational environments.

These findings align with Sarihi et al. (2023), who noted that fuzzy logic systems are particularly well suited to maritime applications owing to their ability to handle imprecise inputs and provide clear, explainable outputs. While this study successfully developed and evaluated a fuzzy logic model for real-time predictive maintenance of the MV Kiboko tugboat engine, several avenues remain for future research. Long-term field validation and deployment of the model in actual vessel operations would generate valuable data on its robustness, adaptability, and impact on reducing engine failures and maintenance costs over time. Comprehensive economic cost-benefit analyses would help quantify the financial implications of adopting fuzzy logic-based predictive maintenance relative to conventional preventive or corrective strategies, supporting investment decisions and broader industry adoption.

Future studies should also explore integrating the fuzzy logic model with advanced sensor networks and Internet of Things (IoT) technologies to enable real-time data collection, cloud-based analytics, remote monitoring, and, ultimately, fleet-wide predictive maintenance. Extending the model to other vessel types, such as cargo ships and passenger ferries, and to other engine systems would help assess its generalizability and scalability across diverse marine environments and operational demands. Hybrid approaches that combine fuzzy logic with machine learning techniques, including neural networks and support vector machines, should also be investigated for their potential to enhance fault-detection accuracy through adaptive learning under complex, nonlinear conditions. In addition, future research should consider incorporating environmental and operational contextual factors such as sea state, weather conditions, and crew behavior; including these variables would provide a more holistic understanding of the influences on engine performance and further improve the accuracy of maintenance predictions.

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