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Development of a fuzzy control system for optimizing fuel consumption on ship main propulsion engines

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Abstract: The maritime industry faces increasing pressure to enhance fuel efficiency and reduce greenhouse gas emissions. Traditional control methods often fail to adapt dynamically to varying sea conditions, leading to suboptimal fuel consumption. This study proposes a fuzzy logic control (FLC) system to optimize fuel consumption in ship main propulsion engines by dynamically adjusting engine parameters based on real-time operational data. The developed FLC model considers key input variables such as engine load, ship speed, and fuel injection timing. The fuzzy inference system comprises fuzzification, rule base, and defuzzification stages. A simulation was conducted in MATLAB/Simulink to evaluate the effectiveness of the FLC compared to conventional control strategies. Simulation results demonstrate that the proposed system significantly improves fuel efficiency. Compared to traditional PID controllers, the FLC system achieves a 5-10% improvement in fuel consumption under various operating conditions. The adaptability of the FLC allows for better fuel optimization and reduction in CO_2 emissions. The proposed FLC system effectively enhances fuel efficiency and can be implemented in marine propulsion systems to support sustainable shipping operations. Future research will focus on integrating machine learning techniques to further refine control precision.
Keywords: *Energy efficiency, Fuel consumption optimization, Fuzzy logic control, Marine engineering, Ship propulsion.*

1. Introduction

The global maritime industry is currently facing significant challenges in terms of energy efficiency and greenhouse gas emission reductions. The International Maritime Organization (IMO) has issued strict policies such as the Energy Efficiency Existing Ship Index (EEXI) and the Carbon Intensity Indicator (CII) as part of its decarbonization strategy for the international shipping sector (IMO, 2021). In this context, fuel saving has become a top priority in ship operations.

The main propulsion engine is the most critical component contributing to a vessel's fuel consumption. Most of the traditional control systems currently in use, such as Proportional-Integral-Derivative (PID) controllers, have limitations in responding to dynamically changing operational conditions such as engine load variations, ship speed, and fluctuating sea states. The inability of conventional systems to handle uncertainties and nonlinearities in the maritime environment leads to suboptimal fuel consumption [1].

With the advancement of intelligent control technologies, fuzzy logic control (FLC) systems have increasingly been explored and implemented in various industrial applications, including marine propulsion systems. FLC is capable of handling uncertainty and system complexity without requiring complex mathematical models. The main advantage of FLC lies in its flexibility to respond adaptively to input variations and its ability to formulate rules based on expert knowledge or system observations [2, 3].

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However, the implementation of FLC in marine fuel-saving contexts is still limited, especially those using real-world operational data from various types of vessels and combining MATLAB/Simulink simulations for performance validation. This research gap forms the foundation of the present study.

This research aims to develop and evaluate a fuzzy logic control system to optimize fuel consumption in ship main propulsion engines based on real operational data. The study also compares the performance of the fuzzy system with conventional PID control under various operating conditions. Hence, this study is expected to contribute to the development of AI-based fuel-saving strategies in the maritime sector.

Several previous studies have explored the application of fuzzy logic in ship propulsion systems. For instance, Wang and Chen [1] developed an FLC system for fuel injection control in marine diesel engines, achieving an efficiency improvement of up to 8% compared to PID control. Kumar, et al. [4] also demonstrated that FLC could reduce fuel consumption in hybrid ship electrical systems by adaptively regulating power distribution.

Zhang, et al. [5] applied a hybrid fuzzy-PID controller to regulate turbocharger pressure in large marine engines, resulting in approximately 7.5% fuel savings. Barros, et al. [6] combined FLC with a genetic algorithm-based optimization system to enhance propulsion efficiency in variable sea conditions.

Other approaches have integrated machine learning with FLC to improve control performance, such as the study by Lee, et al. [7] which applied an adaptive neuro-fuzzy inference system (ANFIS) for energy optimization in marine tankers. However, most of these studies remain theoretical or are limited to a single vessel type.

From these studies, it is evident that:

- FLC has significant potential for improving ship energy efficiency;
- The use of real-world data from multiple vessel types in simulations is rare;
- Comprehensive performance validation of FLC versus PID using MATLAB/Simulink is still limited.

Thus, this study aims to address these gaps by developing an FLC system based on operational data from various ship types and evaluating its performance quantitatively through MATLAB simulation, comparing the fuzzy system against conventional PID control.

With the increasing global focus on reducing fuel consumption and emissions in the shipping industry, optimizing the operational efficiency of main propulsion engines has become a crucial area of research. The International Maritime Organization (IMO) has introduced various regulations, such as the Energy Efficiency Existing Ship Index (EEXI) and the Carbon Intensity Indicator (CII), to enforce stricter fuel consumption controls and emission reductions. These measures push ship operators and engineers to seek more advanced control strategies that enhance energy efficiency while maintaining operational reliability [8].

Traditional ship propulsion control systems often operate based on static settings, leading to inefficiencies when sea conditions, engine loads, and operational parameters fluctuate. These inefficiencies contribute to excessive fuel consumption and increased emissions. Various approaches, including optimal engine load management, hybrid propulsion systems, and real-time monitoring, have been explored to address these challenges. However, conventional control systems, such as PID controllers, struggle with nonlinearities and uncertainties inherent in maritime environments [1, 9].

Fuzzy logic control (FLC) has gained attention due to its ability to handle uncertainty and provide adaptive control solutions. Studies have demonstrated that FLC-based systems outperform traditional control methods in optimizing fuel consumption and reducing operational costs [10, 11].

Several researchers have implemented FLC in energy management and propulsion efficiency optimization in marine systems, showing a fuel savings improvement of up to 10% compared to conventional methods [12-14]. Furthermore, adaptive control strategies such as machine learning and heuristic approaches have been integrated with FLC to enhance real-time decision-making capabilities, making them more robust for practical marine applications [15, 16].

This paper presents the development of an FLC system tailored to optimize fuel efficiency in ship main propulsion engines. The effectiveness of the proposed approach is validated through simulation studies, demonstrating its potential for real-world implementation in the maritime industry.

2. Methodology

2.1. Fuzzy Logic Control System Design

The proposed fuzzy logic control (FLC) system is designed to optimize fuel consumption by dynamically adjusting critical engine parameters based on real-time data. The fuzzy inference system consists of three main components:

1. Fuzzification: Inputs such as engine load, ship speed, and fuel injection timing are converted into fuzzy variables to accommodate uncertainties in operating conditions [17].
2. Rule Base: A set of expert-defined rules governs the relationship between input and output parameters, ensuring that optimal engine settings are maintained under varying loads and operational scenarios [18].
3. Defuzzification: The output is converted back into crisp values to adjust engine operations, optimizing fuel efficiency while maintaining engine stability [19].

2.2. Data Collection and Simulation

Real-time operational data from various ship types were collected, including cargo vessels, passenger ships, and fishing boats. The dataset includes engine power, displacement, fuel flow rate, fuel injection timing, and air-fuel ratio. Table 1 summarizes the key parameters used in this study.

Table 1.
Summary of Ship Operational Data.

Ship Name	Ship Type	Engine Power (kW)	Fuel Flow Rate (L/h)	Fuel Injection Timing (ms) - PID	Fuel Injection Timing (ms) - Fuzzy
KM Nusantara	Cargo	2000	220	22	20
MV Batavia	Passenger	1500	180	18	16
KM Cendrawasih	Fishing	1000	140	14	12
KM Garuda	Tanker	2500	280	28	25
MV Rajawali	Offshore Supply	3000	320	30	27

The simulation was conducted in MATLAB/Simulink to evaluate the effectiveness of the FLC system. The simulation compared the fuel consumption between the conventional PID controller and the fuzzy logic control system under varying operational conditions.

This section outlines the methodology adopted for the development, simulation, and validation of the fuzzy logic control (FLC) system used to optimize fuel consumption in ship main propulsion engines.

2.3. System Architecture

The FLC system is designed with three main components: fuzzification, rule base, and defuzzification. It processes real-time input parameters and outputs control signals that dynamically adjust the fuel injection settings.

1. Inputs: Engine load (%), ship speed (knots), fuel injection timing (ms).
2. Outputs: Adjusted fuel injection timing (ms) optimized for fuel efficiency.

2.4. Data Collection

Operational data were collected from five ship types: cargo, passenger, fishing, tanker, and offshore supply vessels. The dataset includes:

1. Engine power (kW)

2. Fuel flow rate (L/h)
3. Fuel injection timing (ms)
4. Air-fuel ratio
5. Ship speed (knots)

The data were obtained from onboard monitoring systems and logbooks, verified through engine control unit (ECU) records. A total of 300 data entries were gathered per ship type, covering varied sea and load conditions.

2.5. Fuzzy Logic Controller Design

The FLC was implemented in MATLAB/Simulink. The membership functions for each input and output were triangular and trapezoidal in shape. The rule base consisted of 27 expert-defined rules covering various engine load-speed combinations.

1. Fuzzification: Converts numerical input values into fuzzy linguistic variables (e.g., Low, Medium, High).
2. Rule Base: Applies conditional IF-THEN logic. Example:
   IF engine load is High AND ship speed is Low THEN reduce fuel injection timing moderately.
3. Defuzzification: Uses the centroid method to convert fuzzy output back into a crisp control value.

2.6. Simulation Setup

A Simulink model of the engine fuel control loop was developed. Two controller models were simulated:

1. Baseline: Traditional PID controller.
2. Proposed: Fuzzy Logic Controller.

Each controller was tested across a set of 25 different scenarios derived from the operational dataset. Output metrics include:

1. Total fuel consumption (L/h)
2. System response time
3. CO_2 emissions (kg/h) estimated from fuel usage

2.7. Validation

Model accuracy and reliability were validated by:

1. Comparing FLC output to actual data trends
2. Statistical analysis (RMSE, MAE) between FLC and PID results
3. Cross-validation using a 70-30 train-test data split

The goal of the validation is to ensure that the FLC model is not only theoretically effective but also robust across unseen data patterns.

2.8. Fundamentals of Fuzzy Logic Control

Fuzzy Logic Control (FLC) is a form of intelligent control system rooted in fuzzy set theory introduced by Zadeh [2]. Unlike classical binary logic that operates on precise true/false values, fuzzy logic enables reasoning with degrees of truth, allowing systems to handle uncertainties and imprecise data. This characteristic makes FLC ideal for complex, nonlinear systems like marine propulsion engines. A typical FLC system comprises three core stages:

1. Fuzzification: This process converts crisp input values into fuzzy sets using membership functions (MFs). These functions define the degree to which an input belongs to linguistic categories such as “Low,” “Medium,” or “High.”
2. Inference Engine and Rule Base: The fuzzy inference engine applies a set of expert-defined IF-THEN rules to generate fuzzy outputs based on combinations of input conditions.
3. Defuzzification: The fuzzy output is converted back into a crisp value using techniques such as the centroid or weighted average method.

FLC systems are especially effective for control tasks in which the exact mathematical model of the process is unknown or highly complex, as is often the case in marine systems where varying sea states and engine loads affect performance.

2.9. Comparison: PID vs Fuzzy Logic Control

PID controllers are widely used in industrial systems due to their simplicity and proven performance. However, they rely heavily on fixed gain parameters and assume linearity in system dynamics. This makes them suboptimal for systems with time-variant behavior or strong nonlinearities, such as marine propulsion systems operating under changing environmental conditions.

By contrast, FLC offers several advantages:

1. Adaptability: FLC can dynamically adjust to varying input conditions using rule-based decisions.
2. Robustness: FLC systems are less sensitive to noise and parameter variations.
3. No Need for Exact Modeling: FLC does not require precise mathematical models, making it highly suitable for complex systems.

2.10. Energy Optimization in Marine Propulsion

Fuel consumption in ship propulsion is influenced by numerous interdependent variables: engine load, ship speed, fuel injection timing, hull resistance, and sea state. Optimizing energy use requires a control system capable of integrating these variables in real time. Previous studies [6, 7] have shown that AI-based control strategies such as FLC and ANFIS outperform traditional PID in marine energy management. These systems allow for:

1. Real-time adjustments to fuel injection for different sea conditions
2. Energy savings through load balancing and speed optimization
3. Reduction of CO_2 emissions through fuel-efficient engine operation

2.11. Application of FLC to Propulsion Engines

In the context of marine propulsion engines, FLC can be tailored to manage key operational variables. For instance, inputs such as engine load and ship speed can be translated into fuzzy linguistic terms. A rule such as:

"IF engine load is High AND ship speed is Low THEN reduce fuel injection timing"

may reflect operational logic used by experienced engineers. The ability to encode such heuristics into the control system allows FLC to perform well even under highly uncertain and varying conditions.

Moreover, when integrated with real-time monitoring systems, the FLC can continuously adapt engine control parameters to achieve optimal fuel efficiency across multiple voyage conditions.

The theoretical foundation of FLC provides a robust and adaptive control mechanism for marine energy systems. Its ability to mimic human reasoning and manage nonlinear, time-variant systems makes it an ideal candidate for optimizing ship fuel consumption. When compared with PID controllers, FLC offers superior adaptability and performance in dynamic environments.

This theoretical understanding forms the basis for the system design, simulation, and implementation outlined in the following sections of this study.

3. Results and Discussion

3.1. Overview of the FLC-Based Fuel Optimization System

The fuel optimization system is built around a Fuzzy Logic Controller (FLC) designed to dynamically regulate fuel injection timing in marine propulsion engines. The system accepts real-time input parameters such as engine load and ship speed, applies fuzzy inference rules, and outputs optimized fuel injection values. The system was modeled and tested using MATLAB/Simulink.

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3.2. MATLAB/Simulink Environment Setup

MATLAB/Simulink was chosen due to its strong support for fuzzy logic modeling and real-time system simulation. The fuzzy inference system (FIS) was constructed using the Fuzzy Logic Toolbox. The Simulink model incorporates real-time input variables and simulates their impact on fuel consumption. Key components of the simulation model:

1. Engine Dynamics Block
2. PID Controller Block (for comparison)
3. FLC Block (custom rule base and MFs)
4. Monitoring & Data Logging Module

3.3. Membership Function Design

Each input and output variable in the FLC system is defined with three to five membership functions (MFs). Triangular and trapezoidal MFs are used for simplicity and computational efficiency.

Inputs:

1. Engine Load (%): {Low, Medium, High}
2. Ship Speed (knots): {Slow, Moderate, Fast}

Output:

1. Fuel Injection Timing (ms): {Reduce, Maintain, Increase}

3.4. Rule Base Development

The FLC rule base consists of 27 IF-THEN rules derived from expert knowledge and operational behavior of ship engines.

Example Rules:

1. IF Engine Load is High AND Ship Speed is Slow THEN Reduce Fuel Injection
2. IF Engine Load is Medium AND Ship Speed is Moderate THEN Maintain Fuel Injection
3. IF Engine Load is Low AND Ship Speed is Fast THEN Increase Fuel Injection

These rules aim to capture the heuristic strategies used by marine engineers for achieving optimal fuel efficiency.

3.5. Integration with Operational Data

Operational data from five types of ships were used:

1. Cargo
2. Passenger
3. Fishing
4. Tanker
5. Offshore Supply

Data points included:

1. Engine power (kW)
2. Fuel flow rate (L/h)
3. Ship speed (knots)
4. Fuel injection timing (ms)

The data were preprocessed for outliers, normalized, and split into training and validation datasets (70%-30%).

3.6. Simulation Execution

The Simulink model was executed under 25 different load-speed scenarios to simulate realistic voyage conditions. Each scenario was run twice:

1. First with a PID controller
2. Then with the FLC system

Performance indicators captured:

1. Fuel Consumption (L/h)
2. Response Time (ms)
3. CO_2 Emission Estimate (kg/h)

3.7. Design Justifications

1. FLC over ANN or ANFIS: FLC was chosen for interpretability and ease of rule development. While ANFIS provides learning capabilities, it requires larger training datasets and lacks transparency in rule inference.
2. Triangular MFs: Balances simplicity and performance.
3. MATLAB/Simulink: Allows rapid prototyping and accurate modeling of dynamic control systems.

3.8. Fuel Consumption Comparison

Simulation results demonstrate that the proposed fuzzy logic controller consistently outperforms the conventional PID controller in reducing fuel consumption across all ship types. Table 1 summarizes the comparative fuel consumption performance.

Table 2.
Fuel Consumption Comparison (L/h).

Ship Type	PID Controller	FLC System	Improvement (%)
Cargo	230	210	8.7%
Passenger	190	170	10.5%
Fishing	150	130	13.3%
Tanker	290	260	10.3%
Offshore Supply	330	300	9.1%

3.9. CO_2 Emission Reduction

The fuel savings achieved by the FLC system lead to a proportional decrease in CO_2 emissions. Table 2 displays the estimated emission reductions based on fuel usage data.

Table 3.
Estimated CO_2 Emissions (kg/h).

Ship Type	PID Controller	FLC System	Reduction (%)
Cargo	600	550	8.3%
Passenger	500	450	10.0%
Fishing	400	350	12.5%
Tanker	750	680	9.3%
Offshore Supply	850	770	9.4%

3.10. Statistical Evaluation

To validate the robustness of the FLC system, statistical metrics including Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) were calculated between actual data and the predicted control outputs. Results showed that the FLC system had significantly lower RMSE and MAE compared to the PID controller.

3.11. Comparative Analysis with Previous Studies

Compared to Wang and Chen [1] who reported 8% fuel savings using FLC, this study achieved up to 13.3%, attributed to more comprehensive rule base and multi-ship data integration. Similarly, Barros, et al. [6] combined FLC with a genetic algorithm to achieve 10% savings, while our system reached higher efficiency using standard FLC due to better tuned membership functions and validation models.

4. Discussion

The results support the hypothesis that FLC can dynamically optimize fuel injection timing, thus improving fuel economy and reducing emissions. The flexibility of the fuzzy rule base allows the system to adapt better to varying operational conditions than PID controllers. Future work could integrate adaptive learning algorithms into the rule base, such as ANFIS or reinforcement learning models, to further refine system performance.

4.1. Fuel Consumption Analysis

The data collected indicate that the fuzzy logic control system consistently outperforms traditional PID controllers in reducing fuel consumption. Table 4 presents the comparison of fuel consumption between PID and FLC for different ship types.

Table 4.
Fuel Consumption Comparison Between PID and Fuzzy Logic Control.

Ship Name	Fuel Consumption (L/h) - PID	Fuel Consumption (L/h) - Fuzzy	Improvement (%)
KM Nusantara	230	210	8.7%
MV Batavia	190	170	10.5%
KM Cendrawasih	150	130	13.3%
KM Garuda	290	260	10.3%
MV Rajawali	330	300	9.1%

4.2. Environmental Impact and CO2 Reduction

The reduction in fuel consumption directly contributes to lower CO2 emissions, aligning with the global maritime industry's goal of sustainable shipping. Based on fuel consumption improvements, the estimated CO2 reduction per ship type is shown in Table 5.

Table 5.
Estimated CO2 Emission Reduction Using FLC.

Ship Name	CO2 Emission (kg/h) - PID	CO2 Emission (kg/h) - Fuzzy	Reduction (%)
KM Nusantara	600	550	8.3%
MV Batavia	500	450	10.0%
KM Cendrawasih	400	350	12.5%
KM Garuda	750	680	9.3%
MV Rajawali	850	770	9.4%

To rigorously evaluate the performance of the FLC system compared to the PID controller, an extended statistical analysis was conducted. Metrics such as fuel consumption reduction, CO_2 emission reduction, system response time, and controller accuracy were examined in detail. In addition, graphical visualizations were created to support interpretation and highlight performance trends.

4.3. Fuel Consumption Analysis

Fuel consumption data for each ship type were collected and compared for both control methods. Box plots were used to visualize distribution and variance.
The FLC system consistently showed lower median fuel consumption and reduced variance compared to PID, indicating more stable and efficient control.

4.4. CO_2 Emission Trends

Since CO_2 emissions correlate directly with fuel burned, emission trends followed similar patterns.
The FLC system yielded CO_2 reductions of up to 12.5% in fishing vessels and 9–10% in other ship categories.

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4.5. Response Time and Stability

System response time was analyzed to evaluate how quickly each control system reacted to changes in load or speed. The FLC system demonstrated slightly longer initial response but better long-term stability and fewer oscillations.

Table 6.
Average Response Time (ms).

Ship Type	PID Controller	FLC System
Cargo	210	230
Passenger	190	215
Fishing	170	200
Tanker	220	240
Offshore Supply	230	250

Although FLC had slightly longer response times, it avoided overcorrection and system instability.

4.6. Error Metrics: RMSE and MAE

Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) were used to quantify the accuracy of predicted fuel injection values against observed values.

Table 7.
Error Metrics Comparison.

Metric	PID Controller	FLC System
RMSE	5.12	2.87
MAE	3.46	1.94

Lower RMSE and MAE values for the FLC confirm better prediction and control accuracy.

4.7. Multi-Scenario Evaluation

To ensure generalizability, simulations were repeated across 25 randomized operational conditions per vessel type. The FLC consistently outperformed the PID in:

1. Fuel economy
2. Emission control
3. System stability

4.8. Summary of Findings

1. The FLC system offers superior fuel efficiency and CO_2 emission reduction.
2. It maintains better control stability with slightly increased but acceptable response time.
3. Statistical results (RMSE/MAE) strongly favor the FLC approach.
4. Visualization confirms lower fuel usage and higher system reliability.

These findings reinforce the practical advantages of fuzzy control in dynamic marine environments.

4.9. Case Studies per Vessel Type

This section presents detailed case studies of the fuzzy logic control system performance across five representative vessel types. Each case study analyzes fuel consumption, emission trends, and controller behavior under realistic operational scenarios.

4.10. Case Study: Cargo Vessel – KM Nusantara

Operational Profile: Medium-speed cargo ship, operating on coastal trade routes.

- Scenario: Engine load varied between 60%–90%, ship speed fluctuated between 9–14 knots.
- Results:

- Fuel consumption reduced from 230 L/h (PID) to 210 L/h (FLC)
- Emission reduction: 8.3% CO_2
- RMSE improved by 45%; MAE by 47%

Analysis: The FLC system adapted effectively to changing cargo loads and tidal influences, maintaining steady control during acceleration and deceleration.

4.11. Case Study: Passenger Vessel – MV Batavia

Operational Profile: High-speed vessel with frequent docking cycles.

- Scenario: Engine load fluctuated rapidly due to docking maneuvers; speeds between 10–18 knots.
- Results:
- Fuel consumption reduced from 190 L/h to 170 L/h
- Emission reduction: 10.0% CO_2
- System stability improved during stop-start conditions

Analysis: FLC demonstrated robustness during transient operating modes, minimizing fuel spikes during docking and departure.

4.12. Case Study: Fishing Vessel – KM Cendrawasih

Operational Profile: Small vessel with highly variable load conditions, frequent idling.

- Scenario: Mixed operation between trawling, idle, and transit modes.
- Results:
- Fuel reduced from 150 L/h to 130 L/h
- Emission reduction: 12.5% CO_2
- Response time slightly slower, but with more stable fuel regulation

Analysis: The FLC system was particularly effective during variable-speed operations and idling, where PID tended to overshoot.

4.13. Case Study: Tanker – KM Garuda

Operational Profile: Heavy-load, deep-sea tanker with long-duration voyages.

- Scenario: High engine load (80%–100%), speed held constant at 12 knots.
- Results:
- Fuel reduced from 290 L/h to 260 L/h
- Emission reduction: 9.3% CO_2
- RMSE and MAE lower than PID despite consistent load

Analysis: Even under steady-state conditions, the FLC outperformed PID in regulating fuel injection more precisely.

4.14. Case Study: Offshore Supply Vessel – MV Rajawali

Operational Profile: Multi-role ship with variable missions (supply, towing, standby).

- Scenario: Load varied between 40%–85%; frequent speed changes from 6–14 knots.
- Results:
- Fuel reduced from 330 L/h to 300 L/h
- Emission reduction: 9.4% CO_2
- Strongest improvement in load-to-speed adaptation

Analysis: The FLC effectively balanced fuel delivery with demand during mission shifts and standby modes.

4.15. Summary of Case Studies
Across all vessel types:

- The FLC system outperformed PID in fuel savings and emission control.
- It adapted better to variable conditions such as speed fluctuation, docking, and idling.
- Improved accuracy and stability were consistent across diverse operational contexts.

These real-world case evaluations affirm the broad applicability and robustness of FLC in marine propulsion efficiency.

5. Conclusion

This study presents the development and validation of a fuzzy logic control (FLC) system for optimizing fuel consumption in ship main propulsion engines. By utilizing real-world operational data from various ship types and simulating performance using MATLAB/Simulink, the FLC system demonstrated significant improvements over conventional PID control. Key findings include:

- An average fuel consumption reduction of 8.7% to 13.3%, depending on ship type.
- Corresponding CO_2 emission reductions of 8.3% to 12.5%.
- Statistically superior performance in terms of RMSE and MAE metrics.

These results confirm the effectiveness of FLC in dynamically adjusting engine parameters under varying operational conditions. The implementation of such control strategies supports the maritime industry's shift toward greener and more energy-efficient operations. Future research should explore the integration of adaptive machine learning models, such as ANFIS and reinforcement learning, to enhance the intelligence and autonomy of maritime control systems.

This study demonstrates that fuzzy logic control is an effective approach for optimizing fuel consumption in ship propulsion systems. The proposed FLC system provides significant fuel savings and CO2 emission reductions compared to conventional PID controllers. Future research should focus on real-world implementation and integration with machine learning techniques to further enhance performance and adaptability.

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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