

Article

A Novel Approach for the Systematic Evaluation and Optimization of Performance and Emissions in Hybrid Electric Propulsion Systems

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Abstract: In the maritime industry, the adoption of hybrid electric propulsion systems aims to enhance energy efficiency and environmental sustainability. However, this study originates from the fundamental question: ‘Are hybrid systems truly environmentally friendly?’ Ensuring optimal system performance requires accurate load analysis and an effective energy management system. Existing studies have limitations in addressing real-time load variability, long-term load patterns, and scalability across different operational conditions. To address these, this study proposes a standard load analyzer based on main engine power output data to conduct performance analysis. Using MATLAB/Simulink simulations and Excel VBA-based methods, the system evaluates key performance factors under various operational load conditions. Cross-validation between MATLAB and Excel ensured high accuracy, with a relative error rate below 0.01%. The results showed consistent performance indicators, offering reliable insights across vessel types and scenarios. The system’s lightweight design and rapid data acquisition enable effective energy management optimization. However, it has limitations in performing detailed analyses for life cycle assessment, operating expenditures, and capital expenditures. Future advancements in data consolidation and analytical methods will help the tool evolve into a comprehensive tool for multi-dimensional performance evaluation, addressing economic, environmental, and technical aspects.



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Keywords: hybrid electric propulsion system; optimal system performance; energy management system; performance; emission

1. Introduction

In the maritime sector, the implementation of hybrid power systems combining electrical energy with fossil fuels results in significant reductions in emissions and offers promising opportunities within the industry. Hybrid electric propulsion systems in vessels, which incorporate multiple energy sources, provide operational flexibility and economic advantages [1]. However, the variability of these emerging energy sources and the complex interactions involved in their integration with conventional diesel engine systems increase the complexity of managing hybrid electric propulsion systems. A key challenge is ensuring effective coordination between traditional and novel energy systems to establish hybrid

power systems that are stable, reliable, and efficient [2]. However, it faces significant challenges, including load variability, optimal energy distribution, battery SOC management, and generator efficiency maintenance during real-time operations [3].

To overcome these challenges, a comprehensive analysis of the main engine propulsion load data is crucial. These data act as a critical metric for the power management system (PMS), facilitating the determination of the most efficient operational modes [4]. The PMS utilizes these data to optimize the distribution of energy between the generator and the battery, ensuring smooth transitions between operating modes in response to fluctuations in load [5]. Furthermore, the monitoring system provides a real-time visualization of the specific fuel oil consumption (SFOC), power distribution parameters, and battery state of charge (SOC), ensuring the operational stability and dependability of the system [6]. The examination of the main engine propulsion load data extends beyond basic power monitoring, serving a crucial function in attaining energy optimization, operational stability, and adaptability [7]. Additionally, through integration with the energy management system (EMS), it becomes feasible to operate generators within their optimal efficiency zones and facilitate load shifting using energy storage systems [8].

According to research, the lifecycle greenhouse gas emissions of an MGO-based diesel system are 4.22 kg CO₂-eq/km, whereas an optimized hybrid PV/diesel/battery system can achieve emissions as low as 0.75 kg CO₂-eq/km, representing an 82.5% reduction in carbon emissions as shown in Table 1. Impact of charging sources on carbon emissions in electric propulsion ships. However, this value can only be achieved if all conditions are perfectly met, including an optimized design, efficient battery charge and discharge patterns, and a high proportion of renewable energy in the power grid. Conversely, if the battery is charged using the engine’s residual power or through a fossil fuel-based power grid, the carbon emissions in a hybrid system may surpass those of a diesel system. This occurs when the energy flow within the system becomes inefficient, or the engine operates outside its optimal efficiency range. Energy losses during the battery charging process significantly increase the carbon intensity [9].

Table 1. Impact of charging sources on carbon emissions in electric propulsion ships.

System	Carbon Emissions (kg CO ₂ -eq/km)	Energy Source (Charging Source)	Carbon Reduction Rate (Baseline: MGO)
Diesel (MGO)	4.22	Direct diesel engine operation	Baseline (0%)
Hybrid (Baseline)	1.85	Mixed grid (Renewable energy + fossil fuels)	56.2% Reduction
Fossil fuel grid	4.48	Fossil fuel-based grid (coal, natural gas)	6.3% Increase
Renewable energy 79.5%	0.75	Renewable energy grid (solar, wind, hydro, bioenergy)	82.2% Reduction

- Diesel (MGO): Operates exclusively with an engine, offering no carbon reduction benefits.
- Hybrid (Baseline): Utilizes a battery charged from an average mixed grid (renewable + fossil fuels) and achieves a 56.2% reduction in carbon emissions through optimized energy management. The battery is charged from an onshore grid composed of a mix of renewable energy and fossil fuels and operated in an optimized manner.
- Fossil Fuel Grid: Charging the battery solely from fossil fuel sources increases carbon emissions by 6.3% due to energy conversion losses.
- Renewable Energy 79.5%: A battery charged with 79.5% renewable energy achieves an 82.2% reduction in carbon emissions, making it the most environmentally friendly option.

The environmental performance of a hybrid system heavily depends on the energy source used for battery charging. Fossil fuel-based charging increases carbon emissions, while higher renewable energy shares dramatically reduce them. Therefore, effective operation requires optimized energy strategies through EMSs and load analyzers [10].

To overcome these limitations, a load analyzer is essential. The load analyzer analyzes energy usage patterns in real-time to optimize the energy flow between the engine and the battery, ensuring that the engine always operates within its optimal efficiency range [11]. Additionally, it schedules battery charging at times when carbon emissions are minimized and prevents unnecessary energy waste, allowing the hybrid system to fully realize its environmental potential [12].

Jang et al. [13] conducted a load analysis of a 6800 TEU container ship to optimize the generator and battery capacity of an electric propulsion system. Their research converted mechanical propulsion load data into electric propulsion load data and used this analysis to design an optimal generator and battery capacity. The study emphasized improving generator efficiency and distributing loads via batteries to maximize energy efficiency. Oh and Cho [14] analyzed the impact of load fluctuations on the efficiency of hybrid fuel cell propulsion ships. The study utilized AIS (Automatic Identification System) data to monitor load variations during navigation and docking states, highlighting that significant load fluctuations lead to a decline in fuel cell efficiency. The research emphasized the role of a load analyzer, stressing the importance of real-time data monitoring and optimized energy distribution strategies. In conclusion, the study suggested that an accurate load analyzer is essential for ensuring the efficient operation of hybrid electric propulsion systems under varying load conditions, enabling the optimization of fuel cell and overall system performance. The study by Chen et al. [15] aimed to optimize generator capacity and improve energy efficiency through load analysis of shipboard power systems. The study emphasized the importance of real-time load monitoring and accurate estimation of Demand Factors, highlighting that load pattern analysis is essential for optimizing energy management strategies. In particular, the research quantitatively analyzed load variability under different operating conditions (e.g., navigation, departure, anchorage) to identify the necessity of optimizing generator capacity and energy distribution strategies. The study emphasized that the implementation of an accurate load analyzer plays a critical role in achieving operational stability and energy efficiency optimization in shipboard power systems. Zou et al. [16] proposed a real-time energy management approach for fuel cell hybrid electric vehicles (FCHEVs) by developing a discrete optimization method based on game theory. The study highlights the importance of real-time load monitoring and optimization to balance the degradation of fuel cells and batteries while maintaining system efficiency. A key aspect of their research is the load distribution strategy, which considers the competition between fuel cells and battery lifetime. Unlike conventional energy management approaches that focus solely on minimizing fuel consumption, this study integrates real-time degradation quantification models to optimize power distribution between multiple energy sources. The study also emphasizes the importance of considering multiple operational variables, including power fluctuations, fuel cell start–stop cycles, and dynamic load conditions. This aligns with the need for adaptive load analyzers in hybrid propulsion systems, ensuring accurate load prediction and efficient energy management. Banaei et al. [17] explored energy management strategies for hybrid diesel-generator and battery-powered ships operating in multidisciplinary emission policy areas. The study emphasized the need for real-time energy distribution strategies that minimize emissions in restricted zones while maintaining operational efficiency. A nonlinear optimization model was developed using Genetic Algorithms (GAs) in MATLAB to optimize generator output, battery usage, and vessel speed under varying load conditions. The results demonstrated

that strategic load balancing, especially prioritizing battery usage in emission-restricted zones, significantly reduced generator emissions while maintaining cost efficiency.

Existing studies on hybrid electric propulsion systems exhibit several limitations. These limitations include responding to real-time load variability, sophisticated conditional mode-switching algorithms, efficient SOC management, and challenges in long-term load pattern analysis. Furthermore, many studies are confined to specific vessel types or limited datasets (e.g., container ships, cruise ships), restricting their generalizability and scalability. In contrast, this study aims to develop a power load calculator that calculates SFOC based on power load data. This calculator will serve as a tool to numerically analyze fuel consumption and efficiency by processing the data generated during vessel operation. Moreover, the calculator has the potential to be expanded with real-time load analysis, conditional mode-switching, and scenario-based optimization strategies as advanced future applications. These future utilization strategies are expected to ensure broader applicability, superior adaptability, and enhanced performance across diverse vessel types and operating conditions [18]. Building upon this foundation, this paper proposes a MATLAB/Simulink-based marine power system and energy efficiency simulator designed to simplify ship power systems and model essential control algorithms for the PMS. The simulator enables real-time monitoring of power system conditions based on load variations and provides insights into energy consumption patterns and efficiency.

1. Simplified Performance and Emission Monitoring System

Each power source can be scaled and adjusted according to ship design specifications to accommodate different system requirements. The system emphasizes real-time monitoring and analysis of SFOC based on main engine output data. By comparing instantaneous and average SFOC values, it identifies optimal load conditions, reduces fuel waste, and lowers operational costs [19].

2. Engine Performance Improvement

The simulator allows for real-time monitoring of main engine performance, enabling the early detection of abnormalities. This capability supports predictive maintenance strategies and optimal control techniques to minimize downtime.

3. Data-Driven Optimization and Cost Reduction

The simulator optimizes ship operation patterns and strategies based on main engine load data, reducing fuel consumption and operational costs. Additionally, it contributes to carbon emission reductions, ensuring compliance with environmental regulations while improving long-term operational efficiency [20].

2. Methodology

This study aims to develop a standard load analyzer to systematically assess and optimize the performance of hybrid electric propulsion systems. The research methodology consists of three main steps as shown in Figure 1. Systematic methodology framework for standard load analyzer model: developing the load analyzer model, validating the model using real operational data, and analyzing the simulation results, ensuring a structured and comprehensive approach.

2.1. Step 1: Problem Identification and Development of an Evaluation Tool

The first step of the methodology begins with the fundamental question: ‘Are hybrid electric propulsion vessels truly environmentally friendly?’ While hybrid electric propulsion vessels have been highlighted as a sustainable alternative, their environmental benefits across the full life cycle perspective remain insufficiently verified [9]. This is the hybrid

electric propulsion system, using multiple power sources, as shown in Figure 2. Structure of hybrid electric propulsion system with multiple power sources [21].

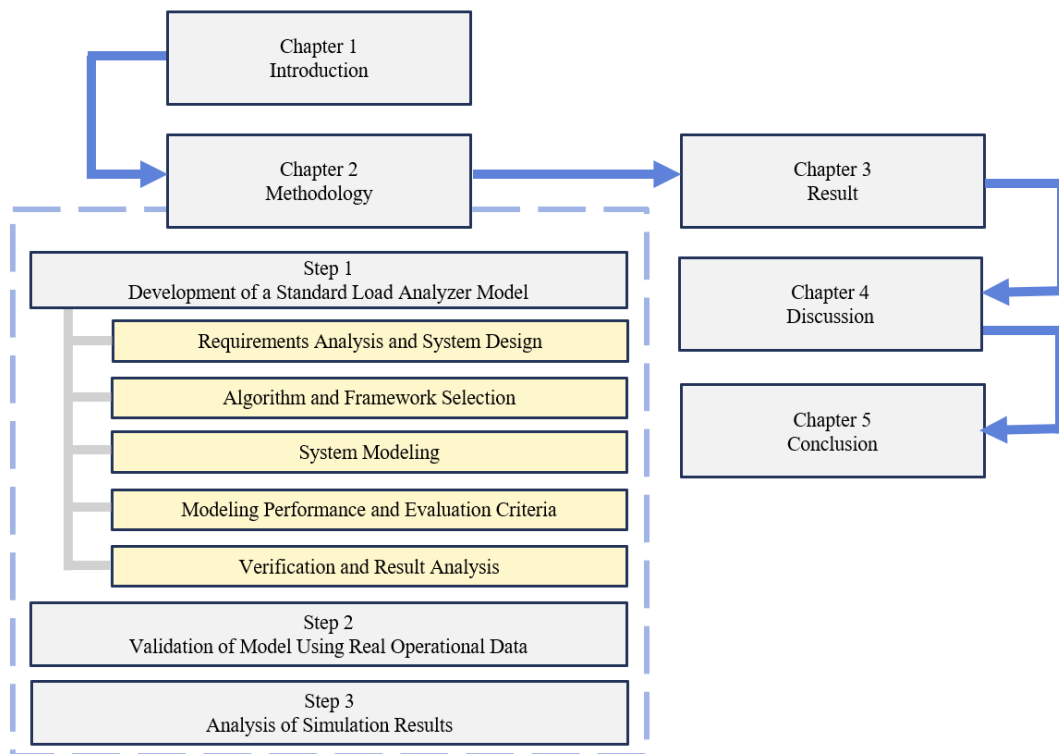


Figure 1. Systematic methodology framework for standard load analyzer model.

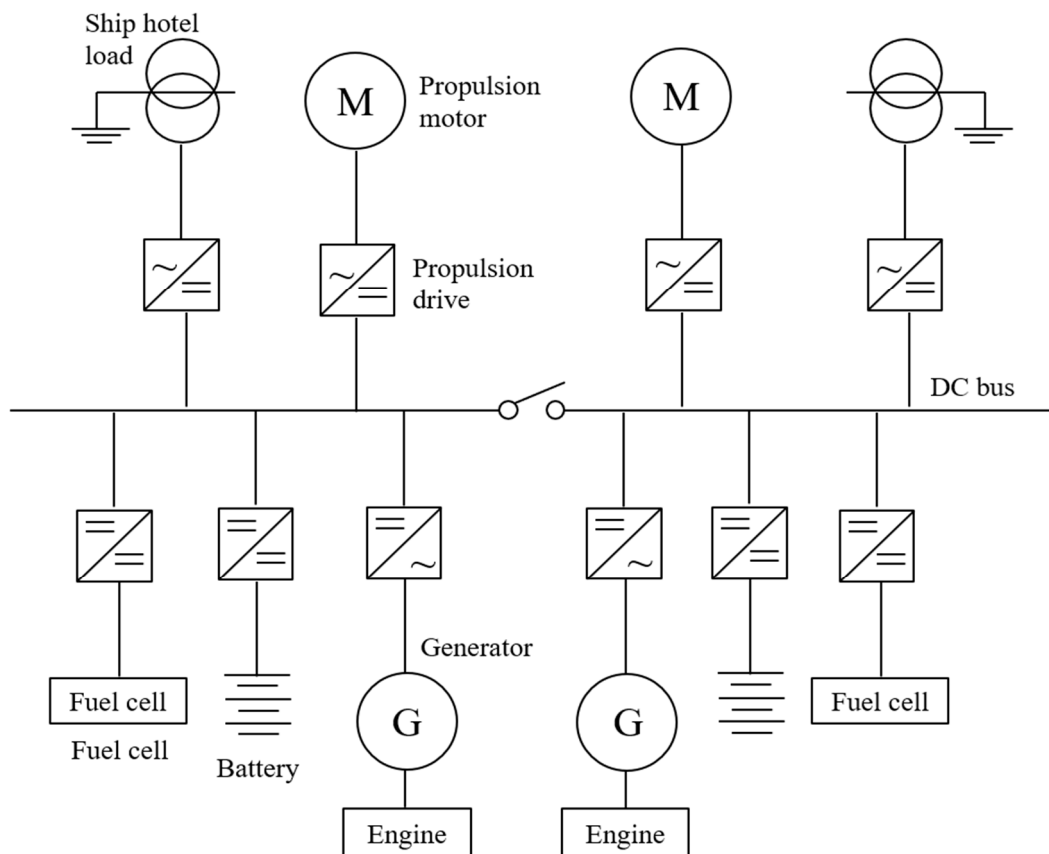


Figure 2. Structure of hybrid electric propulsion system with multiple power sources.

To answer this question, it is essential to monitor and analyze the power output and operational state of the main engine. This involves evaluating how energy is consumed under various operating conditions, determining whether the engine maintains optimal power output, and assessing the resulting environmental outcomes [22]. Such analysis must not be limited to specific hybrid systems, such as battery–engine hybrids, but should be applied to a wide range of hybrid power source combinations [6]. The evaluation tool will be developed using MATLAB/Simulink (The MathWorks, Natick, MA, USA), <https://www.mathworks.cn/products/simulink.html> (1 February 2025), with the main engine power output serving as the primary input for deriving key performance indicators [23].

In this system, the diesel engine generates mechanical power, which is transferred to the generator to produce electrical power for the ship's loads. For the SFOC calculations, the output is measured at the diesel engine's mechanical output to evaluate the engine's efficiency. These data will be continuously monitored and visualized in real-time using the Scope and Data Logging features in MATLAB/Simulink. These visualizations will facilitate the detection of load variations and abnormal operating conditions, providing insights into whether the engine operates within the optimal load range [24].

$$P_W = T \cdot \omega \text{ [Nm} \cdot \text{rad/s]}, \quad (1)$$

$$P_{kW} = \frac{2\pi TN}{60,000} \text{ [kW]}, \quad (2)$$

Subsequently, the SFOC serves as a quantitative metric for evaluating the fuel efficiency of the main engine by measuring the amount of fuel consumed per unit of power output, typically expressed in grams per kilowatt-hour (g/kWh). This parameter is derived from the fuel flow rate and power output data and is continuously monitored in real-time to facilitate comparative analysis against the output SFOC value [3].

$$\text{SFOC} = \frac{\text{Fuel flow [g/h]}}{\text{Power output [kW]}}, \quad (3)$$

The average SFOC value functions as a critical performance benchmark for assessing the long-term fuel efficiency of the engine [25]. It represents the mean fuel consumption rate per unit of power output over a defined operational period and serves as an indicative reference point for determining whether the engine maintains the optimal operational efficiency. Deviations from the optimal SFOC range may suggest engine performance degradation, suboptimal load conditions, or inefficient fuel utilization, necessitating corrective measures to prevent sustained efficiency losses [26].

$$\text{Avg.SFOC} = \frac{\sum \text{SFOC}}{n} \text{ [g/kWh]}, \quad (4)$$

In addition, the total FOC will be analyzed to evaluate the cumulative fuel usage of the engine over a specific period, measured in tons. This metric helps identify fuel consumption patterns, detect inefficiencies during low-load operations, and assess long-term trends in fuel usage.

$$\text{FOC} = \sum_{i=1}^n (\text{SFOC}_i \times P_i \times t_i) \text{ [Ton]}, \quad (5)$$

The total propulsion energy, expressed in kilowatt-hours (kWh), measures the total energy generated by the engine over a specified period. Higher propulsion power with lower fuel consumption indicates efficient engine performance and enhanced operational effectiveness [27].

$$P_{\text{total}} = \sum_{i=1}^n (P_i \times t_i) [\text{kWh}], \quad (6)$$

Lastly, the average power represents the mean power output of the engine over a defined period, measured in kilowatts. This indicator reflects the engine's ability to deliver stable power under varying load conditions [28]. Minimal power output fluctuations and consistent average power levels indicate stable and efficient engine operation. By comparing the average power with the SFOC values, a comprehensive assessment of the engine's operational efficiency can be achieved [11].

$$P_{\text{avg}} = \frac{\sum_{i=1}^n (P_i \times t_i)}{\sum_{i=1}^n t_i} [\text{kW}], \quad (7)$$

The evaluation tool developed in this study will be structured to quantitatively derive and analyze these key performance indicators using the main engine power output data [22]. Through this approach, it will be possible to detect inefficient operating conditions and potential anomalies while providing operational guidelines to maintain the optimal load conditions. Furthermore, the tool is designed to remain adaptable, enabling its application across various hybrid power source combinations and diverse operating conditions without being restricted to specific hybrid configurations [29]. This evaluation tool is expected to serve not only as a performance assessment mechanism but also as a practical decision-support tool for optimizing the operation and energy efficiency of hybrid electric propulsion vessels [30].

2.2. Step 2: Development of Standard Load Analyzer Model

In the second stage, a generalized Load Analyzer model for hybrid marine propulsion systems is developed to serve as a foundational framework adaptable to various operational scenarios [31]. The model comprises key components, including the main engine, PMS, and monitoring system.

2.2.1. Requirements Analysis and System Design

In a hybrid electric propulsion system, the primary role of the load analyzer is to collect, analyze, and visualize engine load data to calculate the accurate SFOC and total FOC. The system must consistently collect and analyze data under various operating conditions, including normal operation, sudden load changes, and low-speed operation; for this purpose, the load analyzer must be capable of stable and lossless data collection and storage, ensuring that critical information is accurately recorded [32]. Furthermore, the collected data must clearly reflect the operational patterns and remain stable and reliable even during sudden load variations [31].

2.2.2. Framework Selection

To establish an efficient load analysis system, the selection of an appropriate framework is essential. Firstly, the load analysis methodology is designed to calculate the SFOC corresponding to each engine load percentage (%) based on the T-Q table. This methodology must process the load data in real-time, minimize errors, and accurately predict fuel consumption patterns in response to load variations. The current system derives the SFOC using an empirical relationship, ensuring practical applicability and alignment with observed operational characteristics.

2.2.3. System Modeling

This step focuses on the development of a standard load analyzer model to systematically analyze the load characteristics of marine power systems [33]. The primary goal is to create a dynamic simulation model capable of assessing load variability, energy consumption patterns, and fuel efficiency [34]. MATLAB/Simulink is utilized as the primary tool for this purpose, enabling quantitative analysis of the main engine power load data under varying operating conditions [35]. The model incorporates key parameters such as SFOC, time intervals (Δt), and real-time load measurements. This step serves as the foundational framework for the subsequent analysis and validation stages, as shown in Figure 3. Simplified scheme of standard load analyzer framework.

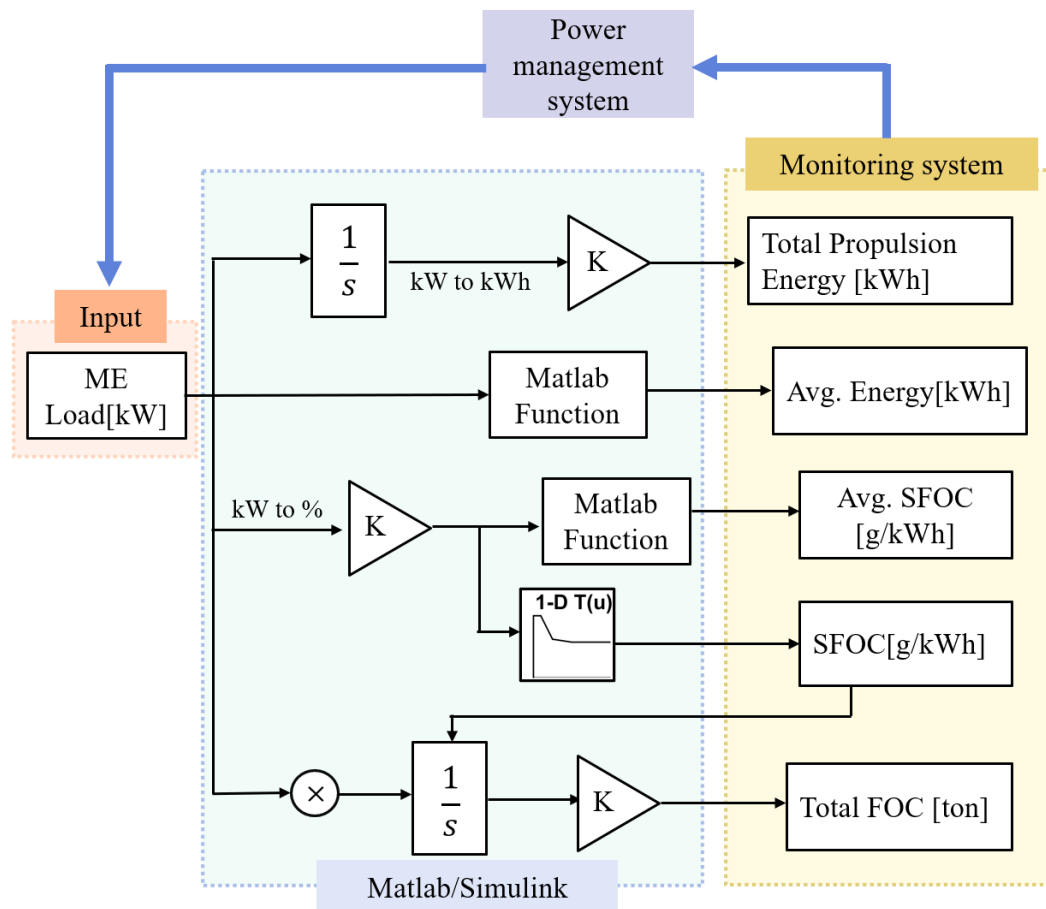


Figure 3. Simplified scheme of standard load analyzer framework.

1. Input Data

These data represent the instantaneous power output generated by the main engine and reflect real-time variations in the load conditions. On actual ships, the power load fluctuates dynamically depending on external factors such as propulsion resistance, weather conditions, waves, and the operational status of power-consuming equipment [36]. However, in this model, the ship operation data are used as the predefined input data to analyze the power system's state and fuel consumption patterns under specific load conditions [37].

2. Monitoring System

The monitoring system is designed to acquire main engine output data from the Main Switchboard and display the real-time values for the output power, instantaneous SFOC, and average SFOC. Additionally, the total propulsion energy and total FOC are objectively displayed through dedicated interfaces, enabling operators to quickly assess the system

status and formulate appropriate operational strategies. This setup establishes a robust foundation for efficiently managing the energy flow of the vessel while maintaining system stability and ensuring optimal performance.

3. Power Management System

The power management system (PMS) is a control system designed to analyze real-time data from the main engine, including the output power, SFOC, total propulsion energy, and total FOC. While the current system is optimized for a single power source, enabling the precise monitoring and optimization of propulsion power and fuel efficiency, it also demonstrates scalability for integration into hybrid systems [38]. In such configurations, the PMS can manage multiple power sources, such as batteries and auxiliary generators, facilitating optimal energy distribution and conditional mode transitions based on varying operational scenarios [39]. Through advanced algorithms and real-time monitoring, the PMS ensures efficient energy flow, minimizes fuel consumption, and enhances system stability [17]. The engine load input data are categorized by time intervals and fed into the model, allowing the replication of various operating conditions, such as normal operation, sudden load changes, and low-speed operation. During the simulation process, the input load data under each condition are analyzed to calculate the SFOC and total FOC. Throughout this process, the consistency between input and output data is validated.

2.3. Step 3: Validation of Model Using Real Operational Data

In this stage, the standard load analyzer model is validated using real operational data from a single vessel [40]. The collected load profile data are fed into the MATLAB/Simulink simulation environment to evaluate the model's performance under stable load conditions and peak load variations across various scenarios [41]. Although hybrid components such as batteries, inverters, and propulsion motors are not included in this analysis to focus on the core functionality of the load analyzer, the proposed model is designed to accommodate these components in future implementation. This flexibility ensures its applicability to a wide range of hybrid powertrain configurations [42].

2.3.1. Application to Vessel

To verify the effectiveness of this load analyzer, one fisheries patrol vessel operating in the coastal waters of South Korea was selected among government vessels. Fisheries patrol vessels primarily carry out missions such as illegal fishing enforcement, marine resource protection, and fisheries guidance and education. Their operational patterns are determined by the nature of these tasks. Fisheries patrol vessels routinely transition between 'run' and 'stop' phases during mission execution, reflecting the inherent variability in their operational profile. These intermittent start-stop cycles induce significant fluctuations in engine output, underscoring the dynamic and variable nature of their operational characteristics. The vessel's key specifications are shown in Table 2. Specifications of main engine on vessel.

Table 2. Specifications of main engine on vessel.

Ship Features	Value
Item	M/E
Unit	2 SET
MCR (Maximum continuous rating)	2190 kW × 800/264 rpm
NCR (Normal continuous rating)	1862 kW × 758/250 rpm
Engine	STX-MAN 6L27/38, 4-Stroke, Diesel

The standard load analyzer proposed in this paper is designed for real-time monitoring. However, due to research environmental constraints, the modeling was validated using actual operational profile data. In this model, the SFOC must be input prior to the load analysis, and the remaining output data can be derived using both the input data and SFOC.

4. Input Data

To validate the standard load analyzer proposed in this study, the operational profile data from a fisheries patrol vessel were utilized. Data were collected and stored at 5 s intervals during the voyage, and it was assumed that the values between intervals remained constant based on the previous data. The collected data served as input parameters for the developed highlighted simulator as presented in Figure 4. Operational profile for target vessel.

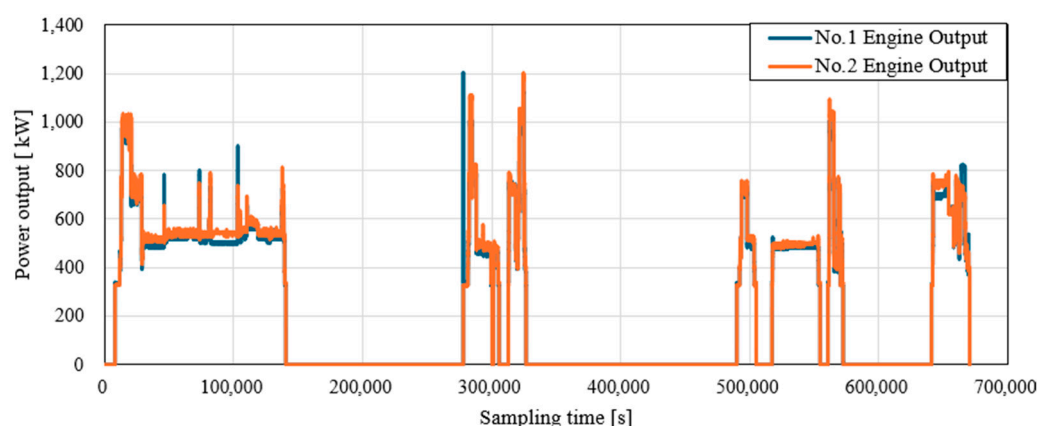


Figure 4. Operational profile for target vessel.

The power source consists of two main diesel engines, each responsible for supplying the total required power allocated to the propeller in the simulator. The power distribution method is assumed to be evenly divided between the two engines as demonstrated in Figure 5. Load profile segmentation based on operational phases.

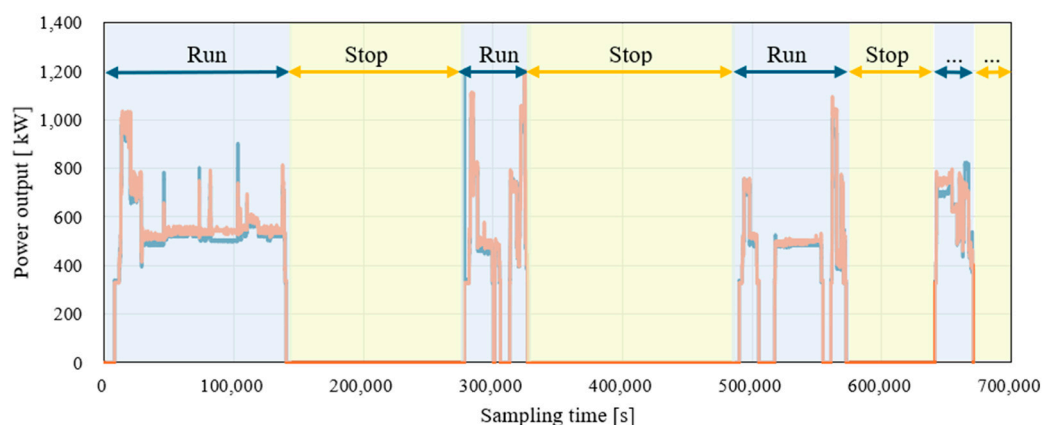


Figure 5. Load profile segmentation based on operational phases.

Due to the operational characteristics of the fisheries patrol vessel, it was observed that the main engine frequently underwent periodic cycles of operation and startup. In the figure, the 'Run' phase is represented in blue area, while the 'Stop' phase is shown in yellow area. During standby periods for port entry and departure, approximately 2000 kW of power was required due to the activation of auxiliary blowers and other auxiliary equipment. During navigation, a maximum power load of approximately 2300 kW (equivalent to 105% for two engines) was recorded. The load profile alternates between

‘Run’ phases, highlighted in light blue and representing active power output, and ‘Stop’ phases, shown in light yellow and indicating idle intervals, both scaled equally on the time axis.

5. Selection and Application of SFOC

To apply the SFOC coefficient in modeling, it is common to use the SFOC data specified in the Engine Performance Data Sheet provided by the manufacturer. However, it is essential to consider engine aging and actual performance degradation. Therefore, to ensure more reliable results, an approach was adopted where the SFOC coefficient was selected based on the data obtained from actual operating conditions [43].

At maximum output (2190 kW) and an RPM value of 800 RPM, the Fuel Index was set to a maximum value of 120%. Using this information, the c-value (0.022813) was derived to calculate the engine power output. Based on these data, the SFOC values were analyzed, as shown below in Table 3. SFOC of target vessels. When compared with the SFOC value specified in the construction specification ($196.73 \pm 5\%$ g/kWh, corresponding to 196.73–206.57 g/kWh), it was observed that the fuel consumption tended to increase due to aging effects [44].

Table 3. SFOC of target vessels.

Power [%]	SFOC [g/kWh]
10	322.3
25	240.8
50	203.3
75	196.7
100	192.2

Additionally, the specific gravity conversion factor (0.86572) provided in the engine sea trial report was applied. The real-time fuel supply and return flow differences, collected through the data monitoring system, were used to calculate the fuel consumption per horsepower-hour. This study focuses on evaluating SFOC under specific engine load conditions using the standard load analyzer. This study primarily focuses on validating the load analyzer using operational data from specific engine power. Additional dynamic parameters, such as speed and torque, can be integrated in future studies to enable a more comprehensive evaluation of engine performance.

2.3.2. Integration of MATLAB-Excel-Real Data Validation

To ensure the reliability and accuracy of the MATLAB model, comparative validation was conducted using MATLAB simulations and Excel VBA-based data analysis methodologies, both derived from the input data representing the vessel’s operational power output. The simulation time in MATLAB was set to start at 0 s and end at 670,680 s, with a sampling time of 5 s applied in a discrete time configuration. This sampling interval was synchronized with the Excel dataset to ensure temporal consistency across both platforms. In the MATLAB model, a 1-D Lookup Table was configured to interpolate data using the Linear Lagrange method. This interpolation method ensures that intermediate values are accurately estimated based on the data points in the lookup table. Additionally, when the input values exceeded the specified range of the table, the model was set to use the last table value. These settings were mirrored in Excel by applying equivalent interpolation and extrapolation techniques within a structured data analysis framework supported by Excel VBA functions. The MATLAB simulations were performed using a variable-step solver with a relative tolerance set to 1×10^{-4} . This solver dynamically adjusted the simulation step size to maintain precision while minimizing the computational load. In Excel, the

same input power data from the vessel were processed through a structured analytical approach utilizing identical sampling intervals and linear interpolation methods, facilitated by Excel VBA-based automation.

3. Results (Step 4: Analysis of Simulation Results)

3.1. Simulation Results

The operational profile data collected were input into the standard load analyzer proposed in this study to conduct simulations. As a result, various indicators, including SFOC, avg. SFOC, total FOC, total propulsion energy, and average energy, were systematically derived. The analyzer accurately reflected the performance indicator patterns, ensuring consistency in the calculation of each indicator.

3.1.1. No. 1 and No. 2 SFOC

The specific fuel oil consumption data derived from MATLAB were validated using the Excel data as a reference. The SFOC represents the instantaneous fuel consumption rate at a specific point in time and varies dynamically over time. It is primarily used to evaluate the instantaneous efficiency of an engine. The objective of this validation was to compare the results obtained from MATLAB and Excel to determine their degree of agreement and to quantitatively assess their consistency. To achieve this, Lin's concordance correlation coefficient was employed. Lin's CCC is a statistical metric that evaluates both accuracy and precision between two datasets by accounting for differences in their means and variances. However, Lin's CCC relies on the Pearson correlation coefficient (r) as a foundational measure of the linear relationship, making it necessary to first calculate the Pearson correlation between the MATLAB and Excel datasets.

The Pearson correlation coefficient (r) quantifies the linear relationship between two datasets, with values ranging from -1 to 1 . A value closer to 1 indicates a strong positive correlation, while a value near 0 suggests no correlation. The formula for the Pearson's correlation coefficient is given by:

$$r = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sum \sqrt{(x_i - \bar{x})^2} \cdot \sum \sqrt{(y_i - \bar{y})^2}}, \quad (8)$$

x_i, y_i : Individual data points from MATLAB and Excel datasets

$\bar{x}, \bar{y}$: Mean values of MATLAB and Excel datasets

While the Pearson's correlation measures the linear association between datasets, it does not account for differences in their means and variances. To address this limitation, Lin's CCC was used to provide a more comprehensive evaluation of the agreement between the MATLAB and Excel results. Lin's CCC is defined by the following formula:

$$CCC = \frac{2 \cdot \rho \cdot \sigma_x \cdot \sigma_y}{\sigma_x^2 + \sigma_y^2 + (\mu_x - \mu_y)^2}, \quad (9)$$

ρ : Pearson Correlation Coefficient (r)

σ_x, σ_y : Standard deviations of MATLAB and Excel datasets

μ_x, μ_y : Means of MATLAB and Excel datasets

The Lin's CCC value quantitatively represents the degree of agreement between two datasets. A CCC value close to 1 indicates perfect agreement, where the two datasets align almost identically in both accuracy and precision. Generally, when the CCC value exceeds 0.95 , it signifies a high level of agreement, suggesting minimal differences and strong consistency between the datasets. Conversely, if the CCC value falls below 0.85 ,

it indicates a low level of agreement, implying noticeable discrepancies that may require further investigation to identify potential sources of error or inconsistency.

The comparison of the MATLAB and Excel SFOC datasets revealed that the Lin's CCC demonstrated a high level of agreement, with an error rate of approximately 0.0005%. This result quantitatively indicates that the SFOC values derived from MATLAB closely align with the reference Excel data as shown in Figure 6. SFOC results for No. 1 and No. 2 main engines. The temporal patterns observed in both datasets showed similar trends, with slight differences primarily attributable to variations in time intervals, data resolution, or calculation algorithms.

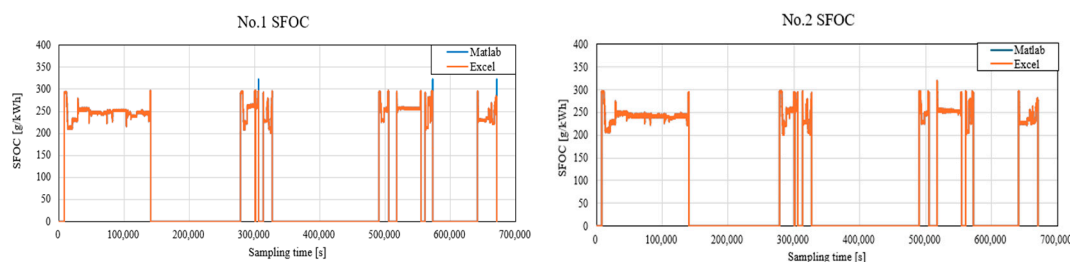


Figure 6. SFOC results for No. 1 and No. 2 main engines.

3.1.2. No. 1 and No. 2 Average SFOC

This average SFOC analysis focused on verifying the consistency between the MATLAB and Excel-based calculation results as presented in Figure 7. Average SFOC results for No. 1 and No. 2 main engines. The comparison revealed a relative error of approximately 0.38% between the two methods. Furthermore, the avg. SFOC graphs for the No. 1 and No. 2 engines showed a stable trend after an initial transient phase, maintaining a consistent pattern throughout the operational period. This indicates that both datasets reliably reflect the engine fuel efficiency and provide consistent results even under extended operating conditions.

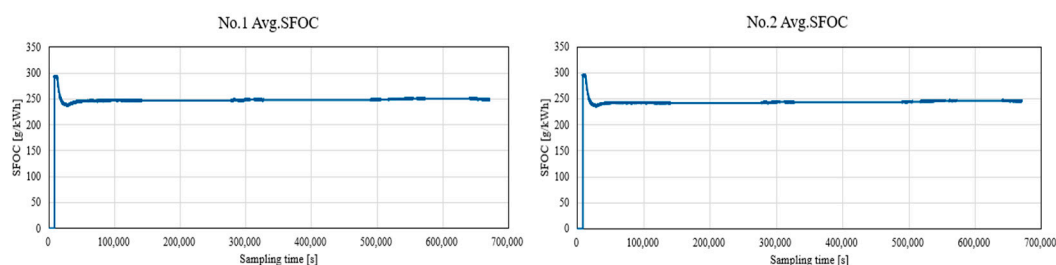


Figure 7. Average SFOC results for No. 1 and No. 2 main engines.

The average SFOC remains consistent even during periods where the instantaneous SFOC values appear as zero due to the engine stop phases. This consistency stems from the calculation method of the average SFOC, which excludes non-operational periods—when both power output and SFOC are zero—from the cumulative sum and count.

Specifically, the average SFOC is derived based on the cumulative fuel consumption and power output during the periods when the engine is actively operating. This ensures that idle or non-operational phases do not distort the overall efficiency measurement. While the instantaneous SFOC reflects transient conditions such as engine stops, the average SFOC serves as a stable indicator of the engine's long-term efficiency throughout the entire operational period. This approach ensures that the average SFOC focuses solely on periods of active engine operation, preventing the distortion effects of non-operational data while maintaining its reliability as a performance metric.

3.1.3. No. 1 and No. 2 Total FOC

This section examines the total fuel oil consumption values derived from the MATLAB numerical integration and Excel cumulative summation, with gain factors applied as unit conversion coefficients to ensure consistency in the comparison as demonstrated in Figure 8. Total FOC results for No. 1 and No. 2 main engines. The analysis focuses on evaluating the numerical difference between the two methods and measuring the extent of variation across the results. With an observed error rate of approximately 0.0005%, the discrepancy is negligible, indicating that both integration and summation approaches produce results that remain well within an acceptable range.

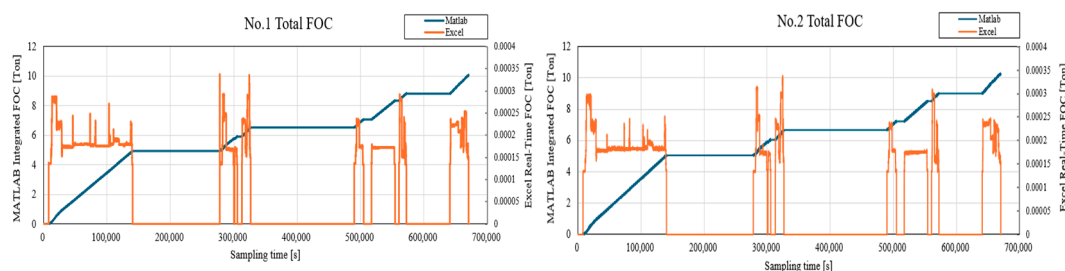


Figure 8. Total FOC results for No. 1 and No. 2 main engines.

3.1.4. No. 1 and No. 2 Total Propulsion Energy

This section investigates the total propulsion energy values derived from the MATLAB numerical integration and Excel cumulative summation, with gain factors applied as unit conversion coefficients to ensure consistency in the comparison. The analysis focuses on examining the overall trend similarity and the accumulated discrepancy between the two methods over time. With an observed error rate of approximately 0.00000006%, the numerical difference remains extremely small, indicating that both approaches produce closely aligned results, as shown in Figure 9. Total propulsion energy results for No. 1 and No. 2 main engines.

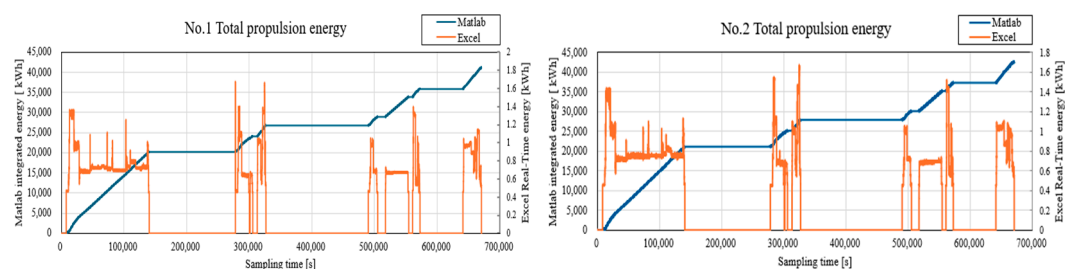


Figure 9. Total propulsion energy results for No. 1 and No. 2 main engines.

3.1.5. No. 1 and No. 2 Average Energy

The average energy analysis aimed to verify the consistency between the results derived from MATLAB and Excel. Both platforms calculated average energy values based on identical input data and demonstrated consistent patterns throughout the simulation period. MATLAB excluded non-operational periods (zero-output phases) from the calculation, ensuring that the average values reflected only the active operational states. This approach prevented distortion caused by idle periods and focused on evaluating the engines' performance under realistic load conditions. In the initial phase, the values exhibited a sharp increase, which can be interpreted as a transient effect occurring during the transition to stable operating conditions. Once the engines reached a stabilized phase, the values maintained a steady pattern, reflecting stable operational performance over time [45].

The results from MATLAB and Excel demonstrated numerical equivalence, indicating that both platforms consistently calculated the average energy values based on the same input data as in Figure 10. Average energy results for No. 1 and No. 2 main engines. This alignment signifies that the calculation processes and outcomes converged reliably, highlighting the robustness and consistency of both methodologies in evaluating average engine performance.

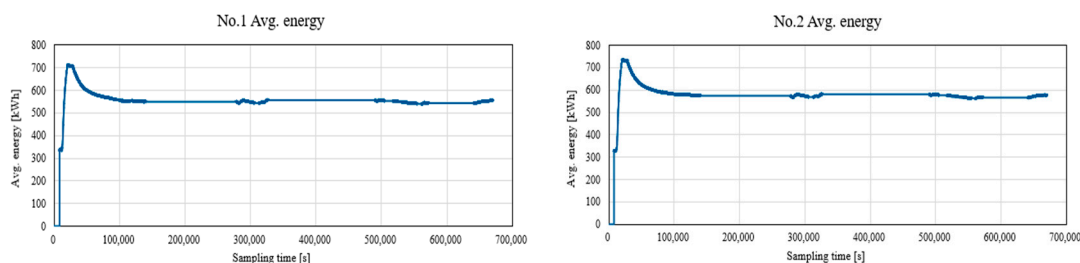


Figure 10. Average energy results for No. 1 and No. 2 main engines.

The analysis confirms that both engines operated with stable and predictable performance across the key indicators, including the SFOC, total FOC, total propulsion energy, and average energy. The stabilization of the SFOC after the initial phase, the linear growth in FOC and propulsion power, and the consistent maintenance of average energy all indicate that the engines effectively met their operational targets without significant deviations or performance losses. These results validate the effectiveness of the standard load analyzer, demonstrating its ability to accurately simulate and model engine performance under various load conditions and operational scenarios.

3.2. Verification with Actual Operational Data

The core novelty of this study lies in deriving quantitative performance evaluations and practical application strategies through data analysis and validation using MATLAB and Excel, based on operational data from marine engines. Unlike previous studies, which often focused on fragmented data analysis or isolated performance indicators, this research integrates the key performance metrics of marine engines into a comprehensive analysis framework, presenting diverse and applicable utilization possibilities. This approach enables quantitative analysis and practical implementation across various aspects, including engine efficiency assessment, battery capacity estimation, operational pattern optimization, and environmental impact analysis, thereby highlighting the study's distinct contribution to the field.

1. Engine Efficiency Assessment and Optimization

Firstly, in terms of engine efficiency assessment, the SFOC and total FOC data were utilized to quantitatively analyze the fuel efficiency. During specific operational intervals, the SFOC values maintained an average of 250 g/kWh, but in certain sections, they increased to as high as 300 g/kWh, indicating an inefficient fuel consumption pattern. These inefficient sections were interpreted as being influenced by factors such as engine load conditions, fuel quality, and operational speed. Through this analysis, strategies for improvement, such as engine load adjustment, fuel injection optimization, and operational speed control, were derived. Additionally, by analyzing the data on a time series basis, it was possible to predict sections where the fuel consumption efficiency would decrease in advance and propose practical optimization measures for operational patterns in those specific intervals.

$$\eta = \frac{\text{Total propulsion power [kWh]}}{\text{Total FOC [g]}} = \frac{1}{\text{SFOC}} [\text{g/kWh}], \quad (10)$$

2. Battery Capacity and Operational Strategy Review

Based on the average energy and total propulsion energy data, the battery capacity and operational strategy for the vessel were evaluated. The analysis revealed that the average power output remained consistently around 570 kW, while the maximum output increased to 730 kW under peak load conditions. Using these results, the required battery capacity for an estimated operational time of 10 h was calculated. This approach helps prevent excessive battery capacity design, which can lead to unnecessary cost increases. Additionally, it allows for the optimization of real-time charging and discharging cycles, effectively extending the battery lifespan. Furthermore, by precisely designing the charging and discharging patterns according to the output fluctuations, the energy management system can ensure efficient power operation, contributing to a more stable and reliable energy supply during vessel operation.

3. Operational Pattern Analysis and Predictive Modeling

Using the total propulsion energy and total FOC data, an operational pattern analysis was conducted, and a predictive model was developed. A comparative analysis between the MATLAB and Excel datasets revealed distinct characteristics in the fuel consumption and propulsion power variations over time. The propulsion power exhibited varying patterns across different segments of the operational timeline and did not remain consistently stable. Meanwhile, the fuel consumption displayed a nonlinear growth trend over time. These insights enabled the identification of specific time intervals and operational segments where the inefficient fuel consumption was concentrated. The findings from this analysis can serve as input data for AI/ML-based predictive modeling, enabling the automation of optimal route and speed adjustments. Furthermore, by integrating various environmental variables such as sea states, weather changes, and load conditions, the predictive model can be refined for more accurate route optimization and operational planning. In conclusion, this analysis goes beyond basic data interpretation by introducing a predictability framework, laying the foundation for enhanced efficiency and stability in vessel operations.

4. Environmental Impact Analysis and Regulatory Compliance

In this study, the total FOC and avg. SFOC data were utilized to quantitatively analyze the CO₂ emissions generated during vessel operations. Fuel consumption (FOC) can be converted into CO₂ emissions by applying the carbon emission factor (EF), which is expressed by the following formula:

$$\text{CO}_2\text{_{-eq}} = \text{FOC} \cdot \text{EF}_{\text{-eq}} [\text{kg} \cdot \text{CO}_2\text{_{-eq}}], \quad (11)$$

where FOC represents the fuel consumption, and EF refers to the carbon emission factor determined by the type of fuel used. These data enabled a detailed calculation of the CO₂ emissions by time intervals and voyage routes, revealing specific patterns of emission spikes during periods of high fuel consumption or reduced efficiency. Such findings can be directly applied to preemptively assess compliance with International Maritime Organization carbon emission regulations.

Over the long term, the continuous accumulation and analysis of these data can facilitate the development of an annual CO₂ emission prediction model for vessels. This model would not only ensure regulatory compliance but also provide a foundational dataset for establishing environmentally sustainable operational strategies. Ultimately, FOC-based CO₂ emission analysis transcends basic calculations, offering critical insights for regulatory compliance, sustainable ship operations, and the formulation of effective carbon reduction strategies [44].

4. Discussion

The standard load analyzer, using main engine output data, was employed to derive and evaluate performance and emission indicators. This approach specifically addresses the fundamental question: 'Are hybrid systems genuinely environmentally friendly?'.

By accurately reflecting engine load fluctuations and fuel consumption patterns, it enables verification of both the environmental performance and economic feasibility of hybrid systems. Unlike previous load analysis tools, which rely on static data and limited variables, the standard load analyzer incorporates real-time data processing and dynamic adaptability. For example, conventional models often assume steady-state conditions, whereas this study accounts for variable sea conditions, load demand shifts, and real-time performance adjustments. This design enhances system flexibility, allowing users to easily modify the parameters as needed. Additionally, this tool provides crucial data for LCA, OPEX, and CAPEX analyses, enabling a comprehensive evaluation of the environmental and economic sustainability of hybrid vessels. Based on this, it is possible to assess the economic feasibility, as well as the impact of fuel type variations and control system design modifications on the environment. It also serves as an essential reference point for battery capacity design and optimal engine configuration, facilitating informed decision-making in the system design phase. This approach prevents unnecessary cost increases caused by excessive battery capacity design and allows for the development of optimized real-time charging and discharging cycles in future research, thereby enhancing battery lifespan effectively. Furthermore, the findings contribute to establishing a strategic foundation for global environmental regulations, such as those set by the International Maritime Organization, supporting improvements in fuel efficiency and fuel consumption reduction. Similarly, the adoption of alarm systems and predictive control mechanisms will play a crucial role in the early detection of anomalies, enabling proactive corrective actions to minimize operational disruptions. Moreover, expanding the standard load analyzer's application to secondary energy sources, such as batteries or auxiliary generators, will optimize load distribution and energy management. The primary objective of this study is to develop a tool to address the fundamental question posed in the research, which necessitates the collection of load profile data from various ship types. These data will serve as a basis for evaluating the superiority of the proposed system over conventional mechanical propulsion systems.

5. Conclusions

This study presents a systematic methodology for evaluating and optimizing the performance of hybrid electric propulsion systems using the standard load analyzer. By utilizing main engine output data, the analyzer effectively monitored performance variations across diverse load conditions and operational scenarios, delivering reliable key performance indicators. Through cross-validation using MATLAB and an Excel VBA-based data analysis methodology, the accuracy and consistency of the analytical results were ensured, with an average relative error rate below 0.01%. This minimal error rate underscores the high degree of alignment between the two platforms and reinforces the reliability of the analytical outcomes. The simulation results clearly demonstrated the capability to quantitatively analyze engine performance and fuel consumption patterns, providing a solid foundation for optimizing the design of hybrid electric propulsion systems and power management systems. Unlike traditional load analysis tools, which are often constrained by parameter complexity, limited flexibility, and slow computational speeds, the standard load analyzer developed in this study features a lightweight architecture, minimal parameter dependency, and high computational efficiency. These core design attributes ensure scalability and adaptability across various hybrid electric propulsion systems and opera-

tional conditions, enabling rapid and precise analytical results. Furthermore, this study highlights the potential for expansion into life cycle assessment, operating expenditure analysis, and capital expenditure analysis. While these analytical frameworks are not yet directly integrated into the current system, advancements in data integration frameworks and interpretation methodologies could enable in-depth and comprehensive evaluations from economic, environmental, and technical perspectives. However, despite its strengths, the current system lacks the direct implementation of LCA, OPEX, and CAPEX analyses, requiring additional frameworks for data integration and result interpretation. Such limitations should be seen not as constraints but as opportunities to advance towards an integrated, multidisciplinary analysis system. If these analyses are effectively integrated in future developments, the load analyzer will be capable of delivering comprehensive and in-depth analytical results across economic, environmental, and technical dimensions. In conclusion, the standard load analyzer transcends the role of a simple load analysis tool; it serves as a strategic platform for hybrid vessel design optimization, operational efficiency improvement, and economic feasibility validation. The high reliability and quantitative accuracy established through the MATLAB and Excel cross-validation signify the potential for further advancements through full-scale sea trials and multi-energy source integration. This system is poised to evolve into a sophisticated analytical platform, driving sustainable innovation and contributing significantly to building a more efficient and environmentally friendly maritime industry.

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