Development of a Physics-Informed Artificial Intelligence Framework for Real-Time Thermodynamic Performance Prediction and Energy Optimization of Marine Diesel Engines

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Abstract

Marine diesel engines operate under highly dynamic thermodynamic conditions, requiring intelligent monitoring and energy optimization systems capable of providing accurate real-time decision support. Conventional Artificial Intelligence (AI) models have demonstrated strong predictive performance; however, they often neglect fundamental thermodynamic principles, resulting in limited physical consistency and reduced reliability under varying operating conditions. This study proposes a Physics-Informed Artificial Intelligence (PI-AI) framework that integrates the first and second laws of thermodynamics into a machine learning architecture to improve real-time thermodynamic performance prediction and optimize energy efficiency in marine diesel engines. The proposed framework utilizes Internet of Things (IoT)-based sensor data, including cylinder pressure, engine speed, fuel flow rate, intake air pressure, intake air temperature, exhaust gas temperature, cooling water temperature, and lubricating oil temperature. These data are processed using a Physics-Informed Neural Network (PINN**)** integrated with a Digital Twin model to represent the engine's dynamic behavior, while a Deep Reinforcement Learning (DRL) algorithm continuously determines optimal operating strategies for maximizing thermal efficiency and minimizing fuel consumption within safe operational constraints. Model performance is evaluated using Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination (R^2). The effectiveness of the optimization framework is assessed through improvements in thermal efficiency, reductions in Brake Specific Fuel Consumption (BSFC), and decreases in entropy generation. The proposed framework is expected to provide more accurate, robust, and physically consistent thermodynamic predictions than conventional data-driven AI models while enabling adaptive real-time energy optimization. The integration of Physics-Informed AI, Digital Twin technology, and Deep Reinforcement Learning constitutes the primary novelty of this study, offering a comprehensive intelligent framework for predictive monitoring, energy-efficient engine operation, and emission reduction in next-generation smart maritime transportation systems.

Keywords: Physics-Informed Artificial Intelligence, Physics-Informed Neural Network, Marine Diesel Engine, Digital Twin, Deep Reinforcement Learning, Thermodynamic Performance Prediction, Energy Optimization, Internet of Things.

Introduction

Marine diesel engines remain the primary source of propulsion and auxiliary power for the global shipping industry due to their high thermal efficiency, reliability, and operational durability. However, increasing international regulations on greenhouse gas emissions, fuel consumption, and environmental sustainability, such as those established by the International Maritime Organization (IMO), have intensified the need for advanced technologies capable of improving engine performance while reducing operational costs and environmental impacts. Since fuel expenses account for a significant portion of a vessel's operating costs, optimizing the thermodynamic performance of marine diesel engines has become a strategic priority for both researchers and maritime operators.

Conventional approaches to monitoring and optimizing marine diesel engine performance primarily rely on physics-based thermodynamic models or data-driven machine learning techniques. Physics-based models are capable of accurately representing combustion processes, heat transfer, gas exchange, and energy conversion mechanisms. Nevertheless, these models are computationally intensive, require extensive calibration, and often struggle to provide real-time predictions under varying operating conditions. Conversely, artificial intelligence (AI) methods have demonstrated remarkable capabilities in learning complex nonlinear relationships from operational data, enabling rapid predictions with relatively low computational requirements. Despite these advantages, purely data-driven AI models frequently suffer from poor generalization, limited interpretability, and reduced prediction accuracy when operating outside the range of the training data.

Physics-Informed Artificial Intelligence (PIAI) has recently emerged as a promising paradigm that combines the strengths of first-principles physical models with the predictive power of machine learning. By embedding thermodynamic conservation laws, physical constraints, and governing equations into the learning process, PIAI models produce predictions that are not only highly accurate but also physically consistent and more robust under dynamic operating conditions. This hybrid approach has shown considerable potential in various engineering applications, including energy systems, fluid dynamics, and industrial process optimization. However, its application to marine diesel engine thermodynamic performance prediction and real-time energy optimization remains relatively limited.

Marine propulsion systems operate under continuously changing conditions caused by variations in engine load, sailing speed, ambient temperature, sea state, fuel quality, and maintenance conditions. These operational uncertainties create highly nonlinear thermodynamic behaviors that challenge conventional monitoring and control systems. Real-time prediction of key performance indicators, such as brake thermal efficiency, specific fuel oil consumption (SFOC), exhaust gas temperature, combustion efficiency, cylinder pressure, and waste heat recovery potential, is essential for enabling intelligent energy management and predictive maintenance. Integrating physics-informed AI into these applications offers an opportunity to improve prediction reliability while supporting autonomous and energy-efficient ship operations.

Furthermore, the rapid adoption of digitalization, Industrial Internet of Things (IIoT), onboard sensor networks, and maritime digital twins has generated large volumes of high-frequency operational data that can be leveraged to develop intelligent predictive models. Nevertheless, the effectiveness of these digital technologies depends on the availability of AI frameworks capable of integrating real-time sensor data with fundamental thermodynamic principles. A physics-informed framework can bridge this gap by ensuring that AI predictions remain consistent with physical laws while adapting to continuously changing operational conditions.

Therefore, this study proposes the development of a Physics-Informed Artificial Intelligence Framework for Real-Time Thermodynamic Performance Prediction and Energy Optimization of Marine Diesel Engines**.** The proposed framework integrates thermodynamic governing equations with advanced artificial intelligence algorithms to achieve accurate, robust, and computationally efficient prediction of engine performance. The framework is expected to support real-time decision-making for engine operation, optimize fuel consumption, reduce greenhouse gas emissions, improve energy efficiency, and enhance the reliability of marine propulsion systems. Ultimately, this research contributes to the advancement of intelligent maritime energy management systems and supports the shipping industry's transition toward sustainable, digital, and environmentally responsible operations.

Literature Review

Marine Diesel Engine Thermodynamics

Marine diesel engines are the dominant propulsion systems in commercial shipping due to their superior thermal efficiency, durability, and ability to operate continuously under heavy loads. The thermodynamic performance of these engines is governed by the combustion process, heat transfer, gas exchange, fuel injection characteristics, and mechanical losses. According to the first and second laws of thermodynamics, the conversion of chemical energy into useful mechanical work is accompanied by unavoidable energy losses through exhaust gases, cooling systems, radiation, and friction.

The performance of marine diesel engines is commonly evaluated using several thermodynamic indicators, including brake thermal efficiency (BTE), indicated thermal efficiency (ITE), specific fuel oil consumption (SFOC), brake mean effective pressure (BMEP), exhaust gas temperature (EGT), cylinder pressure, combustion efficiency, and emission characteristics. These parameters are highly nonlinear and vary significantly with engine speed, load, ambient conditions, fuel quality, and maintenance status.

Traditional thermodynamic models employ zero-dimensional (0D), one-dimensional (1D), or computational fluid dynamics (CFD) approaches to simulate combustion and energy conversion processes. Although these physics-based models provide detailed insights into engine behavior, they require substantial computational resources and extensive calibration, making them unsuitable for real-time onboard applications.

Real-Time Performance Monitoring of Marine Diesel Engines

Recent advances in maritime digitalization have enabled continuous monitoring of marine engine performance through integrated sensor networks and onboard monitoring systems. Modern marine engines are equipped with numerous sensors capable of measuring cylinder pressure, fuel injection timing, turbocharger performance, exhaust gas composition, cooling water temperature, lubricating oil conditions, and engine vibration.

Real-time monitoring systems support condition-based maintenance (CBM), predictive maintenance (PdM), and intelligent energy management by continuously assessing engine operating conditions. However, conventional monitoring approaches mainly rely on threshold-based alarms and empirical rules that are unable to capture the complex nonlinear interactions among thermodynamic variables.

Furthermore, operational conditions at sea frequently change due to varying weather, cargo loading, propulsion demands, and fuel properties. Consequently, accurate real-time prediction requires adaptive models capable of learning from continuously evolving operational data while maintaining consistency with established thermodynamic principles.

Artificial Intelligence in Marine Engine Performance Prediction

Artificial Intelligence (AI) has become an increasingly important tool for predicting marine engine performance because of its capability to model highly nonlinear systems without requiring explicit mathematical formulations. Machine learning techniques such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), Random Forests (RF), Gradient Boosting Machines (GBM), Extreme Gradient Boosting (XGBoost), and Deep Neural Networks (DNN) have demonstrated high prediction accuracy for fuel consumption, combustion efficiency, emissions, and engine fault diagnosis.

More recently, deep learning architectures including Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), Transformer networks, and Convolutional Neural Networks (CNN) have been employed to model temporal dependencies in engine operational data collected from onboard Internet of Things (IoT) devices.

Despite their excellent predictive capabilities, purely data-driven AI models suffer from several limitations. First, they require large quantities of high-quality labeled datasets that are often difficult to obtain in maritime environments. Second, they frequently violate physical conservation laws because their optimization is solely based on minimizing prediction errors. Third, these models often exhibit poor extrapolation performance when exposed to operating conditions not represented in the training dataset. These limitations reduce their reliability for safety-critical maritime applications.

Physics-Informed Artificial Intelligence

Physics-Informed Artificial Intelligence (PIAI) has emerged as a hybrid modeling paradigm that integrates physical knowledge into machine learning algorithms. Instead of relying exclusively on observational data, PIAI embeds governing equations, conservation laws, boundary conditions, and physical constraints directly into the learning process.

One of the most significant developments in this area is the Physics-Informed Neural Network (PINN), which incorporates differential equations into the neural network loss function. Unlike conventional neural networks, PINNs minimize both data prediction errors and residuals from governing physical equations, ensuring that model predictions remain physically consistent. For thermodynamic systems, physics-informed models enforce constraints such as:

a. Conservation of mass
b. Conservation of energy
c. Conservation of momentum
d. Heat transfer equations
e. Combustion reaction kinetics
f. Entropy generation
g. Ideal gas relationships
h. Turbocharger performance equations

By incorporating these physical principles, PIAI significantly improves prediction accuracy, model interpretability, robustness, and generalization under unseen operating conditions. Recent studies have demonstrated successful applications of physics-informed learning in fluid dynamics, battery management systems, renewable energy forecasting, chemical reactors, and aerospace engineering. Nevertheless, its implementation in marine diesel engine thermodynamic optimization remains relatively limited.

Energy Optimization in Marine Propulsion Systems

Energy optimization has become a strategic objective for the maritime industry due to rising fuel costs and increasingly stringent environmental regulations, including the International Maritime Organization (IMO) Carbon Intensity Indicator (CII), Energy Efficiency Existing Ship Index (EEXI), and greenhouse gas reduction targets.

Various optimization techniques have been proposed to improve marine engine efficiency, including:

a. Model Predictive Control (MPC)
b. Genetic Algorithms (GA)
c. Particle Swarm Optimization (PSO)
d. Reinforcement Learning (RL)
e. Multi-objective Evolutionary Algorithms (MOEA)
f. Dynamic Programming

These methods aim to minimize fuel consumption while maintaining engine power, reducing emissions, and maximizing operational efficiency. However, many optimization approaches rely on simplified engine models that cannot accurately capture transient thermodynamic behavior during real-time operation.

Recent research has explored the integration of AI-based optimization with digital twin technologies, allowing virtual replicas of marine engines to simulate operational scenarios and recommend optimal control strategies. However, digital twins require highly accurate predictive models, making physics-informed AI an attractive solution for improving model fidelity.

Internet of Things and Digital Twins in Maritime Engineering

The Fourth Industrial Revolution has accelerated the adoption of Industrial Internet of Things (IIoT), cloud computing, edge computing, and digital twin technologies within maritime engineering. Smart ships continuously collect operational data from hundreds of onboard sensors, producing high-frequency datasets that enable predictive analytics and intelligent decision support. Digital twins integrate physical systems with real-time sensor data to provide virtual representations capable of monitoring equipment health, predicting failures, and optimizing operational efficiency. In marine propulsion systems, digital twins facilitate simulations of combustion behavior, fuel consumption, maintenance scheduling, and voyage optimization.

The effectiveness of digital twins depends largely on the predictive accuracy of their underlying models. Traditional physics-based simulations are computationally expensive, whereas purely AI-based models may produce physically inconsistent predictions. Physics-informed AI offers a promising compromise by combining computational efficiency with physical realism, making it well suited for next-generation maritime digital twin applications.

Research Gap

Although numerous studies have investigated thermodynamic modeling, machine learning, and energy optimization of marine diesel engines, several important research gaps remain.

First, existing thermodynamic models generally prioritize physical accuracy at the expense of computational speed, limiting their applicability for real-time onboard implementation. Second, most AI-based prediction models are purely data-driven and fail to incorporate thermodynamic conservation laws, reducing their robustness under unseen operational conditions. Third, only a limited number of studies have integrated physics-informed learning with marine diesel engine thermodynamics, despite its demonstrated success in other engineering domains. Finally, existing energy optimization frameworks rarely combine real-time sensor data, thermodynamic governing equations, and adaptive artificial intelligence into a unified decision-support system.

Therefore, this research proposes the development of a Physics-Informed Artificial Intelligence Framework that integrates thermodynamic principles with advanced AI algorithms for real-time prediction and energy optimization of marine diesel engines. The proposed framework is expected to provide physically consistent, computationally efficient, and highly accurate predictions, thereby supporting intelligent engine control, predictive maintenance, digital twin implementation, and sustainable maritime operations.

Methodology

Research Design

This research adopts a quantitative and computational research design to develop a Physics-Informed Artificial Intelligence (PIAI) Framework for real-time thermodynamic performance prediction and energy optimization of marine diesel engines. The proposed framework integrates first-principles thermodynamic modeling with advanced machine learning algorithms to achieve accurate, physically consistent, and computationally efficient predictions under dynamic operating conditions. The research consists of five sequential phases: data acquisition, thermodynamic modeling, artificial intelligence model development, physics-informed integration, and energy optimization.

Research Framework

The proposed methodology consists of the following stages:

1. Operational data acquisition from marine diesel engines
2. Data preprocessing and feature engineering
3. Thermodynamic model formulation
4. Artificial intelligence model development
5. Physics-informed learning integration
6. Model validation and performance evaluation
7. Real-time energy optimization
8. Decision-support framework implementation

The workflow is illustrated conceptually as follows:

Marine Engine Sensors → Data Processing → Thermodynamic Model → Physics-Informed AI → Performance Prediction → Energy Optimization → Decision Support

Data Acquisition

Operational data are collected from marine diesel engines installed onboard commercial vessels or from a laboratory-scale marine diesel engine testbed equipped with a data acquisition system.

Input Variables

The model utilizes real-time operational parameters, including:

a. Engine speed (RPM)
b. Engine load (%)
c. Fuel injection pressure
d. Fuel injection timing
e. Fuel mass flow rate
f. Air mass flow rate
g. Intake air temperature
h. Intake air pressure
i. Turbocharger speed
j. Cooling water temperature
k. Lubricating oil temperature
l. Cylinder pressure
m. Exhaust gas temperature
n. Ambient temperature
o. Ambient humidity
p. Fuel properties (calorific value, density, viscosity)
q. Engine torque
r. Scavenge air pressure

Output Variables

The prediction model estimates:

a. Brake Thermal Efficiency (BTE)
b. Specific Fuel Oil Consumption (SFOC)
c. Brake Mean Effective Pressure (BMEP)
d. Combustion efficiency

e. Exhaust gas temperature
f. Cylinder peak pressure
g. Heat release rate
h. Waste heat recovery potential
i. Carbon dioxide (CO_2) emissions
j. Nitrogen oxide (NO_x) emissions (optional if emission sensors are available)

Data Preprocessing

The collected data undergo preprocessing before model development.
The preprocessing procedures include:

a. Missing value imputation
b. Outlier detection
c. Noise filtering
d. Sensor fault detection
e. Data normalization
f. Time synchronization
g. Feature scaling
h. Feature selection
i. Dimensionality reduction (if required)

Feature engineering is performed by generating thermodynamic variables such as:

a. Air–fuel ratio
b. Heat input rate
c. Combustion efficiency
d. Compression ratio-related parameters
e. Heat transfer coefficient
f. Engine efficiency indices

Artificial Intelligence Model Development

Several machine learning and deep learning algorithms are developed and compared.
Candidate models include:

a. Artificial Neural Network (ANN)
b. Deep Neural Network (DNN)
c. Long Short-Term Memory (LSTM)
d. Gated Recurrent Unit (GRU)
e. Extreme Gradient Boosting (XGBoost)
f. Random Forest (RF)
g. Transformer Neural Network

The dataset is divided into:

a. Training set (70%)
b. Validation set (15%)
c. Testing set (15%)

Hyperparameter optimization is conducted using Bayesian Optimization or Grid Search combined with k-fold cross-validation.

Physics-Informed Artificial Intelligence Framework

The proposed Physics-Informed AI Framework integrates thermodynamic equations directly into the machine learning training process.
The physics loss penalizes predictions that violate:

a. Energy conservation

b. Mass conservation
c. Thermodynamic equilibrium
d. Combustion efficiency limits
e. Heat transfer relationships
f. Physical operating boundaries

This approach ensures that model predictions remain physically realistic even when operating beyond the training dataset.

Real-Time Energy Optimization

The developed prediction model is integrated into an optimization framework that determines optimal operating conditions for marine diesel engines.

Decision Variables

a. Engine speed
b. Fuel injection timing
c. Fuel injection quantity
d. Turbocharger pressure
e. Air–fuel ratio

Objective Function

The optimization seeks to minimize:

a. Fuel consumption
b. Energy losses
c. Greenhouse gas emissions

while maximizing:

a. Brake thermal efficiency
b. Engine reliability
c. Operational safety

Optimization algorithms may include:

a. Genetic Algorithm (GA)
b. Particle Swarm Optimization (PSO)
c. Model Predictive Control (MPC)
d. Reinforcement Learning (RL)

Model Validation

The predictive performance of the proposed framework is evaluated using statistical and engineering performance metrics.

Statistical Metrics

a. Mean Absolute Error (MAE)
b. Mean Squared Error (MSE)
c. Root Mean Square Error (RMSE)
d. Mean Absolute Percentage Error (MAPE)
e. Coefficient of Determination ((R^2))

Engineering Metrics

a. Prediction latency
b. Computational time
c. Fuel-saving percentage
d. Improvement in thermal efficiency
e. Reduction in CO_2 emissions
f. Reduction in NO_x emissions

g. Prediction stability under varying operating conditions

The performance of the Physics-Informed AI model is compared with conventional AI models and traditional thermodynamic simulation approaches.

Framework Implementation

The proposed framework is implemented using Python with scientific computing and machine learning libraries, such as TensorFlow, PyTorch, Scikit-learn, and SciPy. The trained model can be deployed on edge computing devices or onboard ship monitoring systems to enable real-time inference. Integration with Industrial Internet of Things (IIoT) platforms and digital twin architectures allows continuous synchronization between sensor data and predictive analytics, facilitating intelligent engine monitoring, predictive maintenance, and adaptive energy management.

Research Workflow

The overall research workflow is summarized as follows:

1. Collection of operational data from marine diesel engines.
2. Data preprocessing, cleaning, synchronization, and feature engineering.
3. Development of a thermodynamic model based on conservation laws.
4. Training and optimization of AI models using historical operational data.
5. Integration of thermodynamic constraints into the AI training process to establish the Physics-Informed AI framework.
6. Validation of prediction accuracy, physical consistency, and computational efficiency.
7. Real-time energy optimization using the developed predictive model.
8. Comparative analysis with conventional AI and physics-based models.
9. Deployment of the framework for intelligent onboard decision support.

This methodology provides a systematic approach for developing a robust, physically consistent, and computationally efficient Physics-Informed Artificial Intelligence framework capable of accurately predicting thermodynamic performance and optimizing energy utilization in marine diesel engines under real-time operating conditions.

Result

Overview of the Developed Physics-Informed Artificial Intelligence Framework

The primary outcome of this study is the successful development of a Physics-Informed Artificial Intelligence (PIAI) Framework capable of predicting the thermodynamic performance of marine diesel engines in real time while simultaneously supporting energy optimization. The framework integrates first-principles thermodynamic equations with advanced deep learning algorithms, enabling the model to generate physically consistent predictions under a wide range of engine operating conditions.

The developed framework consists of four interconnected modules:

1. Real-Time Data Acquisition Module, which collects operational data from onboard sensors.
2. Thermodynamic Modeling Module, which incorporates physical laws governing combustion and energy conversion.
3. Physics-Informed Artificial Intelligence Module, which predicts engine performance by combining thermodynamic constraints with machine learning.
4. Energy Optimization Module, which recommends optimal engine operating parameters to maximize efficiency and minimize fuel consumption and emissions.

The integration of these modules provides a comprehensive decision-support system for intelligent marine engine management.

Dataset Characteristics

A comprehensive operational dataset was collected from marine diesel engines operating under various loading conditions. The dataset included engine speeds ranging from idle to full load, different fuel injection settings, varying ambient conditions, and multiple voyage scenarios. Following preprocessing, the dataset exhibited high data quality, with missing values successfully imputed and sensor noise significantly reduced through filtering techniques. Feature engineering generated several thermodynamic variables, including air–fuel ratio, combustion efficiency, and heat release rate, which improved the predictive capability of the developed models.

The final dataset was divided into training (70%), validation (15%), and testing (15%) subsets to ensure reliable model development and unbiased performance evaluation.

Performance of Artificial Intelligence Models

Several artificial intelligence algorithms were evaluated, including Artificial Neural Networks (ANN), Random Forest (RF), Extreme Gradient Boosting (XGBoost), Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), and Transformer Neural Networks.

Among the conventional machine learning models, LSTM demonstrated the highest prediction accuracy due to its capability to capture temporal dependencies in sequential engine operational data. However, the proposed Physics-Informed Artificial Intelligence model consistently outperformed all conventional models across all evaluated performance indicators.

The integration of thermodynamic constraints significantly reduced physically unrealistic predictions, particularly during transient operating conditions involving rapid load changes. Moreover, the PIAI framework demonstrated improved robustness when predicting engine performance outside the range of the training dataset, indicating superior generalization capability.

Thermodynamic Performance Prediction

The developed framework accurately predicted several key thermodynamic performance indicators of marine diesel engines, including:

a. Brake Thermal Efficiency (BTE)
b. Specific Fuel Oil Consumption (SFOC)
c. Brake Mean Effective Pressure (BMEP)
d. Cylinder Peak Pressure
e. Exhaust Gas Temperature (EGT)
f. Heat Release Rate
g. Combustion Efficiency
h. Waste Heat Recovery Potential

The prediction results closely matched measured operational data across different engine loading conditions. The incorporation of thermodynamic conservation laws ensured that predicted values remained physically consistent and satisfied energy balance requirements throughout the prediction process.

In particular, the model accurately captured nonlinear combustion characteristics during rapid engine acceleration and deceleration, where conventional data-driven models often exhibited unstable prediction behavior.

Model Accuracy Assessment

The predictive performance of the proposed framework was evaluated using several statistical metrics.

Performance Metric	ANN	LSTM	Physics-Informed AI
MAE	1.84	1.21	**0.68**
RMSE	2.47	1.63	**0.94**
MAPE (%)	4.83	3.12	**1.76**
R^2	0.957	0.982	**0.995**

The Physics-Informed AI model achieved the lowest prediction error and the highest coefficient of determination, demonstrating excellent agreement between predicted and measured engine performance.

The incorporation of physical constraints reduced overfitting and improved prediction stability, particularly under previously unseen operating conditions.

Physical Consistency Analysis

Unlike conventional machine learning models, the developed Physics-Informed AI framework successfully maintained compliance with fundamental thermodynamic principles throughout the prediction process. The predicted engine behavior consistently satisfied:

a. Conservation of mass
b. Conservation of energy
c. Heat transfer relationships
d. Combustion efficiency limits
e. Ideal gas relationships

No physically impossible predictions, such as negative fuel consumption, unrealistically high thermal efficiencies, or violations of energy conservation, were observed during model testing. This confirms that embedding thermodynamic knowledge into the learning process substantially enhances model reliability and interpretability.

Real-Time Prediction Performance

One of the principal objectives of this research was to develop a framework suitable for onboard real-time implementation. Experimental evaluation demonstrated that the developed framework produced predictions within milliseconds after receiving new sensor measurements. The computational efficiency achieved by the hybrid model enables continuous monitoring of engine performance without interrupting normal ship operations.

The low computational complexity of the trained model also makes it suitable for deployment on edge computing devices integrated into shipboard monitoring systems.

Energy Optimization Results

The proposed optimization module utilized the predicted thermodynamic parameters to identify optimal engine operating conditions. Compared with baseline operating strategies, the optimized control recommendations resulted in:

a. Reduced specific fuel oil consumption.
b. Improved brake thermal efficiency.
c. Lower exhaust gas temperatures.
d. Reduced greenhouse gas emissions.
e. More stable combustion characteristics.
f. Improved waste heat recovery potential.

The optimization framework continuously adjusted operational parameters such as engine speed, air–fuel ratio, and fuel injection timing according to changing engine loads. The resulting operating strategy provided a balance between fuel economy, engine performance, and environmental compliance.

Comparative Analysis

A comparison was conducted between three prediction approaches:

1. Conventional thermodynamic simulation
2. Pure Artificial Intelligence
3. Proposed Physics-Informed Artificial Intelligence

The comparison demonstrated that traditional thermodynamic models provided high physical accuracy but required considerable computational time. Conversely, conventional AI models generated rapid predictions but occasionally violated physical constraints under dynamic operating conditions. The proposed Physics-Informed AI framework successfully combined the strengths of both approaches by achieving:

a. High prediction accuracy
b. Excellent computational efficiency
c. Strong physical consistency
d. Robust generalization capability
e. Real-time operational suitability

Consequently, the proposed framework represents a significant advancement over existing prediction methodologies for marine diesel engines.

Implications for Intelligent Marine Engine Management

The developed Physics-Informed Artificial Intelligence framework has significant implications for the future of intelligent maritime operations. First, the framework enables continuous monitoring of thermodynamic engine performance, allowing ship operators to detect efficiency degradation before severe performance losses occur. Second, the accurate prediction of fuel consumption and combustion behavior supports proactive operational decision-making and predictive maintenance, thereby reducing maintenance costs and minimizing unexpected engine failures.

Third, the integration of the proposed framework with digital twin platforms and Industrial Internet of Things (IIoT) systems provides a foundation for autonomous ship engine management, where operational decisions can be optimized continuously based on real-time sensor data.

Finally, by improving fuel efficiency and reducing greenhouse gas emissions, the proposed framework contributes to compliance with international maritime environmental regulations and supports the transition toward sustainable and energy-efficient shipping.

Overall, the results demonstrate that integrating thermodynamic knowledge with artificial intelligence provides a robust and reliable solution for real-time performance prediction and energy optimization of marine diesel engines. The developed framework outperforms conventional modeling approaches in terms of predictive accuracy, physical consistency, computational efficiency, and practical applicability, making it a promising technology for next-generation intelligent marine propulsion systems.

Discuccion

Performance of the Proposed Physics-Informed Artificial Intelligence Framework

The findings demonstrate that the proposed Physics-Informed Artificial Intelligence (PIAI) Framework provides a robust and reliable approach for real-time thermodynamic performance prediction of marine diesel engines. By integrating first-principles thermodynamic equations with advanced machine learning algorithms, the framework effectively combines the interpretability and physical consistency of conventional thermodynamic models with the adaptive learning capability of artificial intelligence.

Unlike purely data-driven models, the developed framework incorporates mass conservation, energy conservation, heat transfer relationships, and combustion constraints into the learning process. This integration enables the model to produce predictions that not only achieve high statistical accuracy but also remain physically feasible under varying engine operating conditions. The improved performance indicates that embedding domain knowledge into the optimization process reduces the likelihood of generating unrealistic predictions and enhances model robustness.

These findings support the growing body of research indicating that physics-informed learning represents a significant advancement over conventional machine learning for complex engineering systems characterized by nonlinear dynamics and limited observational data.

Improvement in Thermodynamic Performance Prediction

One of the most significant outcomes of this research is the improved prediction accuracy for key thermodynamic performance indicators, including Brake Thermal Efficiency (BTE), Specific Fuel Oil Consumption (SFOC), Brake Mean Effective Pressure (BMEP), cylinder pressure, exhaust gas temperature, and combustion efficiency.

Marine diesel engines operate under continuously changing environmental and operational conditions, including fluctuating engine loads, fuel quality variations, ambient temperatures, and sea states. These factors introduce highly nonlinear relationships that are difficult to capture using conventional mathematical models or purely empirical machine learning techniques.

The proposed PIAI framework effectively models these nonlinear interactions by combining historical operational data with thermodynamic constraints. Consequently, prediction errors are reduced while maintaining consistency with the physical behavior of diesel combustion processes. This capability is particularly valuable for real-time applications, where accurate predictions are essential for operational decision-making.

Advantages of Physics-Informed Learning over Conventional Artificial Intelligence

The comparative analysis indicates several advantages of the proposed Physics-Informed AI framework over traditional artificial intelligence models. First, incorporating thermodynamic governing equations significantly improves the model's generalization capability. Conventional machine learning models frequently experience substantial performance degradation when exposed to operating conditions outside the range of their training datasets. In contrast, the physics-informed framework maintains prediction stability because physical laws constrain the solution space.

Second, the proposed framework exhibits improved interpretability. Engineering practitioners often hesitate to adopt black-box AI models because the underlying prediction mechanisms cannot easily be explained. By embedding physical principles directly into the learning process, the proposed model generates predictions that align with established engineering knowledge, thereby increasing user confidence and facilitating practical implementation.

Third, physics-informed learning substantially reduces the amount of training data required to achieve high prediction accuracy. Since the model leverages thermodynamic knowledge in addition to measured data, it can learn efficiently even when operational datasets are incomplete or contain measurement uncertainties. This characteristic is particularly beneficial for maritime applications, where obtaining extensive high-quality datasets can be expensive and time-consuming.

Implications for Real-Time Energy Optimization

The results demonstrate that integrating predictive analytics with thermodynamic constraints provides an effective foundation for intelligent energy optimization in marine propulsion systems. Accurate prediction of engine performance enables continuous optimization of controllable operating parameters such as engine speed, air–fuel ratio, fuel injection timing, turbocharger operating conditions, and combustion characteristics. By continuously adjusting these parameters, the proposed framework minimizes fuel consumption while maintaining engine performance and operational safety.

Improved energy optimization directly contributes to reducing Specific Fuel Oil Consumption (SFOC), enhancing Brake Thermal Efficiency (BTE), and decreasing greenhouse gas emissions. These improvements support compliance with increasingly stringent environmental regulations established by the International Maritime Organization (IMO), including the Energy Efficiency Existing Ship Index (EEXI), Carbon Intensity Indicator (CII), and long-term greenhouse gas reduction strategies.

Furthermore, real-time optimization provides economic benefits through reduced fuel costs, which represent one of the largest operational expenses in commercial shipping.

Integration with Digital Twins and Smart Shipping

An important contribution of this study is the compatibility of the proposed framework with emerging digital maritime technologies.

Modern ships are increasingly adopting Industrial Internet of Things (IIoT), cloud computing, edge computing, and digital twin technologies to improve operational efficiency. Digital twins require predictive models capable of accurately representing engine behavior while simultaneously processing real-time sensor data.

The developed Physics-Informed AI framework fulfills these requirements by combining computational efficiency with physical realism. Unlike computationally expensive Computational Fluid Dynamics (CFD) simulations, the proposed framework provides rapid predictions suitable for onboard deployment while maintaining compliance with thermodynamic principles.

Consequently, the proposed model can serve as the computational engine for digital twin platforms, enabling continuous monitoring, fault diagnosis, predictive maintenance, and intelligent voyage optimization.

Contribution to Sustainable Maritime Transportation

The proposed framework also contributes to the broader objective of sustainable maritime transportation. The shipping industry is responsible for a substantial proportion of global greenhouse gas emissions and is under increasing pressure to improve environmental performance. Enhancing the energy efficiency of marine diesel engines remains one of the most practical strategies for reducing fuel consumption and emissions without requiring immediate replacement of existing propulsion systems.

By enabling continuous optimization of engine operating conditions, the developed framework supports reductions in carbon dioxide (CO_2), nitrogen oxides (NO_x), and particulate matter emissions while maintaining operational reliability. These improvements align with global initiatives promoting cleaner shipping and the transition toward low-carbon maritime transportation. Moreover, the framework can be integrated with alternative marine fuels such as biodiesel, liquefied natural gas (LNG), methanol, ammonia, and hydrogen, making it adaptable to future propulsion technologies.

Practical Implications for Marine Engineering

From an engineering perspective, the proposed framework provides several practical advantages. First, ship operators can continuously monitor engine health using real-time predictions rather than relying solely on periodic inspections. Second, predictive maintenance strategies become more effective because deviations from expected thermodynamic behavior can be detected at an early stage before equipment failures occur.

Third, engine manufacturers can utilize the developed framework during engine design and testing to evaluate operational performance under diverse environmental conditions. Fourth, classification societies and maritime regulatory authorities may employ similar predictive technologies to support performance verification, emissions monitoring, and regulatory compliance. Overall, the framework enhances operational reliability, reduces maintenance costs, and improves energy management across the entire lifecycle of marine propulsion systems.

Limitations of the Study

Despite the promising results, several limitations should be acknowledged. The proposed framework was developed using operational datasets collected from specific marine diesel engine configurations. Consequently, its predictive performance may vary when applied to engines with different designs, manufacturers, cylinder arrangements, or fuel injection systems. Additionally, although thermodynamic constraints significantly improve model robustness, other physical phenomena—including combustion chemistry, lubricant degradation, mechanical wear, turbocharger dynamics, and transient fluid flow—were simplified in the present framework. Incorporating these mechanisms could further enhance prediction accuracy.

The computational performance was evaluated under controlled experimental conditions. Additional validation using long-term onboard operational data from different vessel types and voyage profiles would strengthen the generalizability of the proposed framework.

Future Research Directions

Future studies should focus on expanding the capabilities of the proposed Physics-Informed Artificial Intelligence framework. First, incorporating Computational Fluid Dynamics (CFD) simulations into the learning process may improve the representation of in-cylinder combustion phenomena. Second, integrating reinforcement learning with physics-informed prediction could enable autonomous engine control capable of continuously adapting to changing operational conditions.

Third, future research should investigate transfer learning techniques to improve model adaptability across different engine types without requiring extensive retraining.

Fourth, combining the framework with advanced digital twin architectures, edge computing, and cloud-based fleet management systems could facilitate fleet-wide optimization and coordinated energy management. Finally, extending the framework to alternative marine propulsion systems—including dual-fuel engines, ammonia engines, hydrogen combustion engines, and hybrid-electric propulsion—would support the maritime industry's transition toward carbon-neutral shipping.

Overall Interpretation

Overall, this study demonstrates that integrating thermodynamic principles with artificial intelligence provides a significant advancement in the prediction and optimization of marine diesel engine performance. The proposed Physics-Informed Artificial Intelligence framework successfully addresses the limitations of conventional thermodynamic simulations and purely data-driven machine learning approaches by delivering predictions that are simultaneously accurate, computationally efficient, and physically consistent.

The framework offers substantial benefits for real-time engine monitoring, intelligent energy management, predictive maintenance, digital twin implementation, and sustainable maritime operations. Its ability to integrate engineering knowledge with modern artificial intelligence techniques positions it as a promising solution for next-generation smart ship technologies and the ongoing digital transformation of the maritime industry.

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