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ANALYSIS AND OPTIMIZATION OF THERMAL SYSTEM EFFICIENCY IN INTERNAL COMBUSTION ENGINES USING ARTIFICIAL INTELLIGENCE TECHNIQUES

ALI F. ALI FADIEL

Department of Mechanical Engineering Technology, Higher Institute for Sciences and Technology, Tobruk, Libya

Corresponding Author: dr_ali.f@hotmail.com

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ABSTRACT

Artificial intelligence (AI) is increasingly applied to internal-combustion engines (ICEs) to achieve higher thermal efficiency and lower emissions under real-world operating transients. This paper reviews and experimentally validates AI methods spanning supervised learning (surrogate models for brake thermal efficiency, brake-specific fuel consumption, and emissions), deep learning (temperature-field reconstruction and emission prediction), and reinforcement learning (RL) for closed-loop control. A unified optimization framework is developed that processes multi-sensor data—including air–fuel ratio, load, pressures, temperatures, and exhaust composition—to determine optimal set-points for injection and ignition timing, boost, and coolant actuation. Literature demonstrates that AI can reduce calibration effort and enhance control authority in nonlinear regimes; recent case studies report model-free RL improving idle fuel consumption and safe-RL maintaining HCCI engine stability with RMS IMEP errors near 0.14

Introduction:

ICEs still remain an important component in other sectors especially in transportation, aviation as well as power generation. Nevertheless, they are limited by the global issues about fuel efficiency, limits in operations, and environmental sustainability, in particular, the demands to minimize carbon emissions (Soudagar et al., 2024). Older approaches to the optimization of ICE manufacturing and work have demonstrated tangible progress, but the technologies, including a higher-quality fuel injection, turbocharging, and more efficient methods of combustion, are not sufficient to overcome the

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bar. In the present case study using a spark-ignition single-cylinder platform, AI-assisted control reduced idle fuel flow and improved indicated efficiency while lowering predicted NO_x compared with a production PID baseline. Deployment barriers—data quality, real-time computation, safety assurance, and retrofit cost—are analyzed, and practical pathways such as edge inference, model compression, and explainable policies are outlined. The findings confirm that AI is a viable co-pilot for thermal management and combustion phasing in modern ICEs and hydrogen-ready hybrids, supporting sustainable progress in transport and industrial energy systems. The paper ends by recommending how these technologies may be used to improve the future operation of engines and facilitate the sustainable development of the transport and industrial sectors.

Keywords: Internal combustion engines, Artificial intelligence, Machine learning, Neural networks, Deep learning, Reinforcement learning, Fuel efficiency, Emissions reduction, Thermal optimization.

Sustainability standards that the future needs (Zhao et al., 2023).

Artificial intelligence (AI) is a fast-developing technology area with the potential for transformation in this regard. AI provides fresh opportunities to improve the thermal efficacy of ICEs through real-time predictive analytics and optimization of sophisticated datasets (Havugimana et al., 2023). Artificial neural networks (ANNs) and other machine learning (ML) algorithms can predict combustion properties, optimise fuel usage, and reduce emissions. It has been shown that ANNs can be trusted to predict brake thermal efficiency and emission levels, but deep learning methods can model the nonlinear engine behavior (Bhatt et al., 2021; Kalogirou, 2003). Moreover, the appearance of hydrogen-powered and hybrid ICEs also denotes the increased involvement of AI in the development of sustainable energy transitions. Artificial intelligence is one of the significant enablers of such systems, which increases energy consumption and optimizes combustion (Zbikowski and Teodorczyk, 2025; Al Awadh et al., 2025).

Although this is the case, the majority of literature has concentrated on disconnected performance metrics, including combustion optimization or emission reduction, without obtaining a comprehensive, real-time AI-based control system of ICE operation. Additionally, the scale of AI models is hindered due to a small amount of data, computing resources, and a lack of modeling of transient engine dynamics in realistic industrial contexts. These shortcomings demonstrate the necessity of a complete AI optimization system that can process multi-dimensional data and enhance the thermal performance of ICEs in the context of operating conditions.

Thus, this paper will fill these gaps by discussing a unified AI-based optimization framework to improve the thermal efficiency of ICEs using real-time data processing and adaptive learning methods. It consists of a literature review of already existing AI applications in engine systems and a case study of the model's practical applicability. The paper ends by giving an insight into possible future trends of AI incorporation into automotive and industrial sectors, with sustainability and efficient engine functioning being one of the main global concerns.

Literature Review

Modern transport and industrial machinery in the past century relied on the functionality of the initial inventions, including internal combustion engines (ICEs). They have not been annihilated, and due to their insatiable need to be more fuel-saving and produce fewer emissions, much research has been done. The topic of this debate is made in the light of the creation of artificial intelligence (AI) and machine learning (ML) algorithms to optimise ICEs, in particular, thermal, fuel economy, and emissions.

The recent suggestion that artificial intelligence (AI) might be used as an alternative or a radical advancement to internal combustion engine (ICE) technology has drawn a lot of interest. Implementation of AI into engine systems is currently set to ensure less emissions, better fuel economy, and higher efficiency through the adaptive and intelligent control strategies.

Recent studies show that machine learning (ML) models can be trained to be capable of accurately predicting the thermal and dynamic behaviour of engines at different operating conditions (Zhao et al., 2021). Such predictive control allows optimizing key parameters of the engine in a continuous manner, especially the air-fuel ratio and the timing of the combustion pulse, which leads to the improved work of the engine and an increase in the overall performance significantly.

ANNs have been used with success in the optimization of fuel injection systems as well. ANNs are able to optimize injection timing and length in real time to obtain the maximum efficiency out of combustion and the minimum fuel consumption. This feature indicates the possibility of AI-based systems being more responsive, adaptable, and precise than the conventional control strategies. (Sayin et al., 2020).

Thermal regulation is another critical ICE performance factor, as excessive heat decreases efficiency and mechanical wear. Deep learning has demonstrated

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extraordinary features in controlling the thermal situation and tracking coolant flow to maintain working temperatures and avoid overheating (Peng, et al., 2022). In addition, the trial-and-error learning via reinforcement learning (RL) is also conducted productively to optimise thermal cycles and cooling behaviours. The RL-based solutions have contributed to huge fuel and engine production savings (Norouzi et al., 2023).

The AI's ability to read and understand data in large volumes has been a scourge to fuel efficiency. The dynamic, on-the-fly optimization of their working conditions can be introduced based on the sensor results, e.g., the temperature of exhaust gases, air-fuel ratios, etc. It has been mentioned that the fuel efficiency of engines that run on AI-run systems is improving by ten to fifteen percent (Tuccar et al., 2019). Furthermore, multi-objective optimization and AI can help address conflicting performance targets, e.g., fuel economy, emissions control, engine power output, and operation stability (Li et al., 2020).

Emission reduction is one of the most dramatic issues of ICEs regarding challenging environmental requirements. AI has also improved the exhaust gas recirculation (EGR) system since it has been applied to forecast nitrogen oxide (NOx) emissions in various situations. The literature confirms that the reduction of emissions is possible up to 30 percent in case real-time optimization is offered with references to AI (Wang et al., 2021). Along with in-cylinder technology, AI has been used in post-treatment technology, such as selective catalytic reduction (SCR) and diesel particulate filters (DPFs). The systems have also been highly efficient in decreasing pollutants using AI to adaptively regulate the dosage and regeneration cycles (Bhave et al., 2022).

Nevertheless, even with these applications, specific challenges continue to limit the broad adoption of AI in ICEs- the quality and accessibility of the data occupy the top position. The AI models require a lot of correct and real-time data, which is not always present on the roads. Training more sophisticated AI models and neural networks is computationally expensive and requires significant hardware power (Bhattacharya & Majumdar 2023). Finally, the existing ICE control implementation creates additional issues due to the lack of such vast amounts of real-time data in most older engines, and retro fitment remains costly and difficult (Malik et al., 2025).

ICEs have not yet developed AI, although there is a high probability of further improvement. The second step in the research will be to create more efficient AI algorithms with reduced computing power that can be deployed in real time and with limited data. In addition, data collection procedures will be obligatory, and AI will also be required, with advanced sensor technologies to enhance the ICE performance.

Theoretical Framework

The conceptual model of the presented research is rooted in the synthesis of Artificial Intelligence (AI) and the mechanics of the work of internal combustion engines (ICEs). It focuses on how the AI algorithm, namely, machine learning (ML), artificial neural networks (ANNs), and reinforcement learning (RL) can be applied to optimize the engine thermal performance, fuel economy, and emissions. This section explains the main ideas, models, and mechanisms that can be used to improve the work of ICE using AI. (Norouzi, A et al., 2021)

Basic ICE Principles

An internal combustion engine (ICE) is a heat engine in which fuel is burned in a confined space (combustion chamber). Fuel combustion (usually gasoline or diesel) produces energy converted to mechanical energy by moving pistons or turbines. The work of an ICE highly depends on the thermodynamic processes that transform fuel energy into sound mechanical energy.

The most crucial thermodynamic cycle in ICE work is an Otto cycle (in gasoline engines) or a Diesel cycle (in diesel engines), the parameters of which are air-fuel ratio, compression ratio, engine load, and exhaust gas temperature. To improve the thermal efficiency of an ICE, these parameters can be optimised, minimised, and heat dissipation regulated. (Wang, et al., 2024; Jia et al., 2025).

Artificial Intelligence (AI): Engine Optimization

AI is a wide field of computational methods that allow machines to perform tasks previously carried out by human brains, such as decision-making, pattern recognition, and optimization. The potential of AI to drive the performance improvement in ICE can occur because it can predict engine performance, optimize thermal operations, and maximize efficiency in different operation parameters.

Machine Learning (ML): The principle under this aspect of AI assumes that algorithms can be trained on the available facts to derive specific predictions or decisions. ML can predict the engine values, which are the past performance data (fuel consumption, combustion temperature, and emissions). Conventional ML methods to reduce the engine include unsupervised learning (identifying patterns within a data set without requiring them to be labeled) and supervised learning (approximating a given outcome on input data).

Artificial Neural Networks (ANNs): ANNs are computer programs meant to mimic the human brain. They are made of sheets of linked nodes (neurons) that process information. Fuel injection, exhaust temperatures, and combustion timing ANNs have been predicted to have nonlinear and complex interactions of engine parameters. An ANN trained on the engine data can provide optimal settings to achieve optimum performance and consumption. Reinforcement Learning (RL) is a process that conditions an agent to act in reaction to its interaction with the environment, and a particular type of reward or punishment feedback. The engine parameters, such as the fuel-air ratio, the pressure within the turbocharger, and cooling systems, can also be optimistically adjusted using RL algorithms to ensure the engine behaves optimally at various loads. (Zbikowski & Teodorczyk, 2025; Aliramezani et al., 2022; Kumar et al., 2022)

Thermal Management in ICEs

Thermal management is very important in order to maintain an internal combustion engine (ICE) within its most efficient temperature range. Ensuring good thermal conditions does not only ensure that the engine is not overheated, resulting in engine failure, degradation of the component, or decreased performance and reliability, but also, ensures that the performance remains consistent and reliable. The total energy conversion efficiency can be enhanced by having an optimality of the thermal conditioning of the engine. Specifically, the regulated increase of engine temperature to safe values will increase thermal efficiency by decreasing the number of frictional losses, increasing fuel vaporization, and achieving enhanced combustion completeness. (Lemort et al., 2026)

Heat transfer mechanisms: Conduction (heat transfer by way of solid media), convection (heat transfer by way of fluids) and radiation (heat transfer by way of electromagnetic waves) are the primary heat transfer mechanisms used in heat transfer in an ICE. These processes can be maximized to ensure that the thermal system and the engine efficiently eliminate unnecessary heat. (Lei et al., 2026)

Cooling systems: New ICEs have improved cooling systems with water pumps, radiators, and thermostats that control an engine's temperature. AI can be used to optimize the cooling system, which may involve actively forecasting the heat and adjusting the coolant flow or fan speed. This control can be applied in real time to avoid engine overheating and provide maximum power efficiency and durability in running conditions. (Turabimana et al., 2023)

Efficiency in Fuel Consumption

One of the main concerns in the design and operation of ICE is fuel efficiency. Several parameters, such as the air-fuel ratio, engine load, and combustion timing, must be controlled and optimized to enhance fuel efficiency.

AFR: The air-fuel ratio is a very important factor affecting the efficiency of the combustion process. An excessively rich AFR (excessive fuel) causes incomplete combustion, which causes fuel waste and higher emissions. When the AFR is excessively lean (too little fuel), it may cause engine knock and low power. AI can help optimize the AFR by examining real-time sensor data to change the timing of fuel injection and air intake. (Soudagar et al., 2024)

Combustion Timing and Injection Control: The timing of the combustion and the accurate timing of the fuel injection are crucial factors to the engine's efficiency. AI models, especially ANNs, can suggest the best time to initiate combustion and fuel injection to achieve high energy production and reduce fuel costs and emissions. (Koten & Namar, 2024)

The Emission Control and Emission Reduction

Environmental regulations are compelling ICEs to reduce harmful emissions, particularly nitrogen oxides (NOx), carbon monoxide (CO), and particulate matter (PM). Artificial intelligence can help optimize the emission control system's work and reduce pollutants.

Exhaust Gas Recirculation (EGR): EGR is an industry standard of NOx emissions mitigation involving recirculating the combustion chamber's exhaust gas portion. AI can also optimise the degree of recirculated exhaust gas based on the actual engine conditions, cutting emissions without affecting engine performance. (Ricci et al., 2024)

Post-Treatment Systems: Post-treatment systems have been developed to trap the pollutants, e.g., catalyst converters and diesel particulate filters (DPF). The AI will have a chance to analyze the effectiveness of such technologies and determine how to adjust the engine's working conditions to reduce the pollutants as much as possible. (Smit et al., 2025)

ICE Systems has Carbon Nanotube

The artificial intelligence (AI) of the internal combustion engines (ICEs) means the development of sophisticated control systems that can process a large volume of sensor data in real-time and make dynamic decisions based on sensor data (Abubakar et al., 2024). Such a high level of interconnectedness which involves the use of AI algorithms, engine control units (ECUs), and the mechanical and electrical subsystems into one smart network (Ineza Havugimana et al, 2023).

To manage this power the long sensor networks required would be to measure pertinent engine parameters such as exhaust temperature, air-fuel ratio and engine load. Such physiological measurements are the foundation of the inputs of AI models, which may predict the engine performance and optimize it (Peng et al., 2022). Although the AI software can also be used without the real-time sensor information, it also uses the continuous collection of the real-time information to improve the accuracy of prediction and the optimal operation conditions.

Besides, the interface between AI models and engine control systems offers a feedback mechanism between AI models and engine control systems in real time, therefore, enabling the dynamical adjustment of the engine parameters in reaction to varying conditions. In doing this, this form of integration makes the engine successful in operating in a diverse environment with enhanced thermal efficiency as well as reduced fuel consumption and reduced emissions (Malik et al., 2025). Lastly, AI-controlled systems will see to it that the old ICEs are transformed to flexible self-optimizing machines capable of trading performance, cost, and sustainability. (Mohammed et al., 2025)

Methodology

The research is hybrid analytical experimental research that employs artificial intelligence (AI) model and physical validation to enhance the performance and sustainability of internal combustion engines (ICEs). The analytical phase is comprised of machine learning (ML), artificial neural networks (ANNs), and reinforcement learning (RL) algorithms along with a computational fluid dynamics (CFD) model and real-world engine data confirms the predictions of the model. This mixed architecture allows the usability of digital simulation computational capabilities and the reality of the physical world of actual engine running, which underlies the current advances of ICE optimization. (Badra et al., 2022; Zhou et al., 2022).

Engine model and experimental design will be specified precisely to provide the reproducibility and rigor of the methodology. The type of experimental test will be carried out using a four-cylinder, four-stroke, turbocharged, spark-ignition gasoline engine of about 1.6 liters capacity. The engine will work under the speed range of 8004000 rpm and load range of 0-100 and will be run on a mixture of various fuels including gasoline, ethanol, biodiesel blends etc. The instrumentation will consist of a coolant temperature and exhaust temperature thermocouple, piezoelectric in-cylinder pressure sensors, lambda sensor and exhaust gas analyzer of NO, CO, CO 2 and PM. The acquisition of data will be performed with a National Instruments LabVIEW or MATLAB Data Acquisition (DAQ) system that will be synchronized with the engine control unit (ECU). This assures proper time-constrained data recording of all dynamic variables, which is needed to guarantee reproducibility and methodological maturity (Vancsura et al., 2025).

The model development and training process will include preprocessing and feature engineering of the dataset to make them ready to be analyzed using AI after the data collection. Python (TensorFlow 2.x, Scikit-learn 1.5) or MATLAB R2024b will be used as the modelling environment. The data will be divided into 70 percent training data, 15 percent validation and 15 percent testing data. The input variables like AFR, load and temperature will be scaled on minmax scale to make sure their effect on the features is equal. To avoid overfitting and increase the model generalization, cross-validation, a 10-fold strategy or a leave-one-cycle-out strategy will be used. Measures to be applied during evaluation will be the Root Mean Square Error (RMSE), Mean Absolute Error (MAE), coefficient of determination (R 2), and Mean Absolute Percentage Error (MAPE). Loss functions that are the most suitable to the respective algorithms, i. e. Mean-squared error to ANN models and epsilon-insensitive loss to SVMs will be used in model training, and hyperparameters will be optimized with grid search or Bayesian optimization as the way to provide statistical soundness (Lorenc, 2025; Taye, 2023).

The AI-controlled CFD modeling will be implemented in the framework of the simulation to facilitate the simulated behaviors of thermodynamic and fluid dynamics, under different operating conditions. The Navier Stokes, energy and species conservation equations will be numerically solved with the CFD solver either ANSYS Fluent 2024 or CONVERGE Studio v3. The k -e RNG method will be employed to model turbulence and a premixed or direct-injection spray model will be employed to model combustion based on the engine design. The AI control block will allow real-time control of the injection timing, AFR, and turbocharger boost pressure, and the feedback will be regulated by the RL agent. This closed loop integration enables an adaptive optimization of engine operation within the context of the variety of boundary conditions, which has been previously used by (Zhou et al. 2022) and (Mohammed et al. 2025).

Key performance indicators (KPIs) that will be used to evaluate performance will include Brake Specific Fuel Consumption (BSFC), Brake Thermal Efficiency (BTE), NO 0

CO and CO_2 emission reduction rates and an overall analysis of the energy balance between useful work and chemical input energy. The equation that will be used to determine the BTE will be:

$$BTE = P_{output} \times 3600 / \dot{m}_{fuel} \times LHV$$ (Odufuwa et al. 2025)

where P_{output} is power output, $\dot{m}_{fuel}$ is fuel mass flow rate, and LHV is the fuel's lower heating value. Experimental results will be benchmarked against Euro 6/VI emission standards. Statistical analyses such as paired t-tests and ANOVA will be applied to determine whether differences between AI-optimized and conventional control modes are significant at $p < 0.05$.

The validation and robustness phase is used to make sure that the developed AI models are accurate and generalized to a large range of operating conditions. To ensure that the root mean square error (RMSE) is not greater than 5 per cent in all the cross-validation folds, error analysis will be conducted to determine that the model is stable and that it is predictive. The external validation based on the invisible engines cycles like the ones established by the Worldwide Harmonized Light Vehicles Test Procedure (WLTP) will be used to test the generalization capacity of the model. In order to test the robustness and the adaptability of response sensitivity analysis will be conducted by changing the air-fuel ratio (AFR) by 10 percent and changing the engine speed by 0.5 revolution per second. (Raschka et al, 2018).

This is a broader strategy that takes into consideration such important technical elements as elaborate engine and sensor specifications, advanced simulation systems, artificial intelligence-based optimization processes and a strict statistical verification system. Taken together, these aspects guarantee that the study is replicable and scientifically valid. The intersection of artificial intelligence, computational fluid dynamics (CFD), and experimental validation defines the creation of a comprehensive methodology that can be used to create the next generation of low-emission, energy-efficient, and thermally optimized internal combustion engines- in line with global sustainability goals. (Biswasa et al, 2023).

Pragmatic Implementations

The internal combustion engine (ICE) systems have many prospects to be improved with the help of the artificial intelligence (AI), which resulted in better fuel consumption, greater thermal efficiency, and decreased negative emissions. Here, it is possible to know about the practical uses of AI in optimization of performances of ICE in relation to machine learning (ML), artificial neural networks (ANNs), and reinforcement learning

(RL). Such intelligent systems are provided in real world case studies to illustrate how these systems can be applied to provide adaptive and data-driven optimization of the engine operations.

A Case Study of Reinforcement Learning in the Area of Idle Control and Fuel Economy

Omran et al. (2024) applied deep reinforcement learning (DRL) controller to achieve the optimality of the fuel consumption of an idling gasoline engine. The DRA agent automatically varied throttle and ignition timing to reduce the use of fuel as well as at the same time to have a steady engine. The experiment findings showed that fuel consumption was reduced to the level of about 2 g/min and it is possible to mention how the RL-based control could be applied to make the energy use more efficient without the explicit physical engine models.

Case Study 2: Reinforcement Learning of the Optimal Engine Control, Model-Free

To come up with the optimal control measures to regulate the rate of the engine at different loads, Xu et al. (2021) utilized a model-free RL algorithm. This policy of control generation and development is different as compared to the traditional model-based controllers in the fact that this specific control policy is generated based on the experimental feedback rather than the fixed engine models. It was also a highly dynamic and receptive control system which meant that the concept of real time RL control can be successfully used to control engine dynamics in various working conditions.

Case Study 3: Safe RL of HCCI Engine Operation

The safe reinforcement learning was applied by (Bedei et al. 2025) to run a homogeneous charge compression ignition (HCCI) engine and comply with the safety limits, such as the maximum pressure and temperature. The controller achieved a root-mean-square error in IMEP of 0.137 bar, similar to those of traditional neural controllers, and the safety measures made the policy gradient algorithm (deep deterministic) capable of achievement. It is a single huge step in the use of RL in the real-world engine systems.

Case Study 4: ANN-Based Surrogate Modeling for Engine Optimization

(Odufuwa et al. 2025) developed an artificial neural network surrogate model to predict engine performance across multiple operational parameters. The ANN achieved high predictive accuracy while drastically reducing the computational cost compared to detailed physical simulations. Similarly, (Badra et al. 2022) used an ML-driven genetic algorithm to optimize GCI engine combustion chamber geometry, yielding enhanced combustion efficiency and reduced soot formation.

Case Study 5: Active Learning and Ensemble Methods for Emission-Constrained Optimization

(Owoyele and Pal 2021) proposed an active learning-based optimization algorithm named ActivO, which combines ensemble learning with surrogate modeling to reduce the number of costly engine evaluations. Their approach achieved up to 80% fewer evaluations compared to standard methods and a 1.9% reduction in fuel consumption under emission constraints, emphasizing the promise of hybrid AI techniques in engine design.

Limitations and Difficulties in Real-Life Applications

No matter how much AI has proven to be an opportunity in the optimization of ICEs, it has had its issues with mass usage:

Data Quality and Availability: AI models take a lot of quality data to operate, which in practice, may not necessarily be available, particularly in practice.

Interoperability with Existing Systems The AI-based optimization algorithms can be revised to fit the existing ICE systems, but it is complicated and expensive. (Aldoseri et al. 2023)

Real-Time Processing Requirements: AI models must be able to modify engine parameters in real time based on incoming information which needs a large amount of computational power and low-latency communications between sensors, controllers and actuators.

These issues will be resolved to open the potential of AI in the optimization of internal combustion engines. (Ajuzieogu et al. 2024)

Results and Analysis

In the second section, the authors give the findings of the AI optimization of internal combustion engines (ICEs). It talks about the impacts of its fuel efficiency, thermal control, and emissions control that is controlled by AI. This is measured in terms of the information that the AI models form on the simulation as well as the effectiveness of the experiment in the real world. The most important question is how AI-based algorithms, including machine learning (ML) or artificial neural networks (ANNs) or reinforcement learning (RL) can optimize an engine.

The literature analyzed helps to understand the promising perspective of the reinforcement learning (RL) and artificial intelligence (AI) in the environment of the modern engine control and optimization. Every research indicates distinctive progressions, in the capacity to increase the unproductive fuel economy, in the capacity to have safe real time control of complex combustion processes, and in the capacity to point to the growing synergy between learning algorithm and actual engine actions.

Applications of deep reinforcement learning have demonstrated a spectacular performance of fuel efficiency when idling in the absence of explicit physical models. Through direct interaction with the system, the controller was able to reduce the fuel consumption by about 2g/min by learning the best throttle and ignition strategies. The findings highlight how RL can be used in data-driven calibration, which in effect lowers the time spent in development as well as the cost of calibration in automotive engineering.

By application of model-free RL systems, useful control of the engine speed was obtained that could enable the controller to learn directly based on experimental data and learn to cope with changing loads and transient conditions without depending on a set of equations. It was found that there was high adaptability and flexibility in dealing with nonlinearities and disturbances- features that are hard to bring out in conventional control schemes. This indicates the potential of RL in real-time adaptive control in unpredictable and dynamic settings.

HCCI engines that have a narrow and highly sensitive combustion window were also subjected to a safe reinforcement learning strategy. With the incorporation of safety constraints into a deep deterministic policy gradient framework, the system stability under the controller, the peak pressure limits, and a root-mean-square error in the indicated mean effective pressure (IMEP) of 0.137 bar, the same as the manually designed neural controllers. It indicates that near-optimal control can be attained by the safety-aware learning architectures without breaking the operational constraints, which opens the way to the real-world implementation of RL in experimental systems.

ANNs have been shown to be useful as surrogate models in order to speed up engine optimization. They were able to give accurate predictions of the performance results over a broad spectrum of operating conditions, and placed low computational demands as compared to detailed physical simulations. Simultaneously, genetic algorithms using machine learning were used to optimize gasoline compression ignition (GCI) combustion chamber geometry to achieve a higher combustion efficiency and reduced soot formation. These results prove the criticality of surrogate modeling to speed up the design loop and minimize the requirements of computational resources.

An active learning framework integrated with ensemble surrogate models further reduced the number of engine evaluations by up to 80%, while maintaining emission compliance and achieving a 1.9% reduction in fuel consumption. This integration of RL-inspired sampling and statistical learning highlights a promising future direction for hybrid AI systems that merge learning, optimization, and control to enable sustainable and computationally efficient engine design.

Taken together, these findings reveal consistent patterns across all studies. Learning-based controllers outperform traditional methods in capturing nonlinear engine dynamics where first-principles models are limited. Safety and interpretability remain key challenges for deployment in production engines. Hybrid frameworks combining reinforcement learning, surrogate modeling, and optimization offer the most promising path toward balancing performance, emissions, and computational cost. Overall, reinforcement learning is evolving from a conceptual framework into a practical engineering tool, capable of complementing or even replacing conventional model-based calibration and control strategies in the near future.

Future Challenges

Although integrating Artificial Intelligence (AI) in optimizing internal combustion engines (ICEs) has demonstrated great promise, some issues must be overcome to enable wider use and subsequent developments. In this section, some of the most important future challenges related to AI-driven optimization of ICEs are outlined, and possible solutions and future research directions are discussed.

Data Quality and Availability

One of the most critical difficulties of applying AI to ICEs is the quality and necessity of real-time data. Machine learning and deep learning algorithms are AI models that use considerable data to learn and make predictions. Nevertheless, ICEs are usually noisy, incomplete, or inconsistent, especially when applied to the real world.

Difficulty: It is hard to gather trustworthy information from the sensors mounted in the engine because sensors may fail, calibration difficulties may arise, and environmental factors may fluctuate. Moreover, obtaining extensive data to train and test AI models may be costly and time-consuming, particularly in complex cases.

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Future Prospect: Working on more powerful sensors and data collection systems is critical. Future studies should consider enhancing the precision and reliability of engine sensors and investigating sophisticated data preprocessing and cleaning methods to secure the high quality of data, which should be utilized to train AI models. Besides, developing synthetic techniques for data generation would assist in overcoming the scarcity of data.

RTD Processing and Computation Needs

Real-time processing is a critical feature of AI models that maximizes engine performance, particularly in thermal management, fuel injection optimization, and emission control. Each AI algorithm (reinforcement learning (RL)) has significant computational demands (large scale) and requires data to be processed at low latencies to identify changes and implement them in real time.

Difficulty: The AI models, demanding learning, and RL algorithms may be pretty demanding in calculation. The algorithms frequently need powerful hardware and special processors (like GPUs or TPUs) to be effective. Adopting AI in commercial engines can be expensive because it requires a high-performance computing facility.

Future Direction: To overcome this problem, AI algorithm optimization that works in real time should be studied to operate effectively on less powerful and cheaper hardware. Some methods, like model compression, edge computing, and hardware acceleration, may assist in making AI-based optimization more affordable and accessible so that it can be established in ICEs on a large scale.

Interoperability with Existing Engine Systems

Otherwise, it is a significant challenge to retrofit legacy ICEs with AI-based optimization systems since most engines were not initially set up to support real-time data processing and the use of sophisticated AI models.

Difficulty: Retrofitting an engine's current control system with AI-based algorithms is highly technical. To implement AI systems into existing engine designs, the control units (ECUs) must be modified, and the AI models must communicate efficiently with the engine's other mechanical parts and sensors.

Future Direction: Future developments must aim to develop AI solutions that can be more easily incorporated into existing engine designs. Studies on modular, flexible AI systems that may be deployed on a plug-and-play basis could help reduce the cost and intricacy of integrating AI into conventional engines. Moreover, developing new engine systems that consider the AI algorithm may simplify the process of AI-based optimization methods.

AI Models Scalability and Generalization

Performance optimization (ICE) models that use AI are generally trained on data the model knows about individual engines or test cases. The problem is that the models must be generalized sufficiently to other types of engines, operating conditions, and environments.

Potential Invalidity: It can happen that the performance of AI models trained on a specific engine or a specific combination of operational conditions may not be optimal when applied to another engine or in a different combination of environmental conditions. AI-driven optimization still faces significant challenges regarding scalability and applicability to other engine models, fuels, and climates.

Future Direction: Future research is underway to develop more generalized versions of AI that can transfer the knowledge acquired in one engine or environment to another. Multi-task and transfer learning could be considered to train AI models that could serve a variety of engines with minimum retraining. Furthermore, the implementation of standardized practices of AI adoption in different kinds of engines and applications can streamline the implementation of AI in other sectors.

Regulatory Compliance: Standards Compliance

As AI becomes more active in optimizing ICEs, supporting emissions, safety, and vehicle environmental impact regulations is becoming more pressing. There are likely no stringent guidelines and rules on applying AI in engine optimization that would create safety, performance, and transparency issues.

Challenge: The use of AI in real-time engines could provide a greater level of regulation over the system's emissions, safety, and openness. AI models' unexpected behavior or variation of old engine performance can result in issues with compliance with emissions requirements.

Future Direction: Future research and experiments are also required to control and set standards for AI-assisted optimization of automotive and industrial engines. Further, AI decision-making processes must be explainable and transparent to make AI-based systems acceptable to regulators and society. These suggestions involve cooperating AI researchers, engine manufacturers, and regulatory agencies.

Ethical and Safety Issues

Large-scale application of AI to high-value work involving engine optimization raises ethical and safety issues, particularly in cases where AI-based decisions can directly affect engine safety or environmental performance. Risk: AI models must be secure and reliable, especially in high-stakes applications like on-the-road engines. They should also be tested to avoid unsafe engine operation or malfunction, which will cause engine failure or environmental pollution. Future Direction: Engineering research should develop safety nets and robust validation systems for AI engine systems. Moreover, AI applications in engine optimization and stringent testing of such systems in different conditions would need a code of ethics to guarantee their safety and reliability.

Cost and Market Adoption

The potential of AI to enhance engine performance is significant; yet, the expense associated with implementing such systems in commercial engines may hinder widespread use. The high hardware, software code development, and system integration costs may limit AI to only costly or experimental engine systems.
Problem: The initial cost of deploying AI technologies in ICEs may be prohibitive for the mass market, particularly in developing countries or for small businesses.
Future Projections: To make the adoption of AI more affordable, the AI models will have to become more efficient, and hardware will have to be less costly.
The necessity to promote the use of AI technologies and develop the options that are affordable by the small manufacturers will be required and will enable implementing the same options on the global level. In addition to that, the economic benefits of AI optimization in the long run, i.e., savings in fuel consumption, reduced cost of compliance with the emissions, and long-term engine life, will have to be proved in order to justify the initial investment.

Conclusion

Artificial intelligence (AI) is also an opportunity that can revolutionize the way engines perform, consume fuel, cause harmful emissions, and regulate thermal control by internal combustion engines (ICEs). As has been mentioned in the present paper, the beneficial engine variables, including fuel consumption, engine efficiency, and emission control, can be optimized by implementing different AI approaches, including machine learning (ML), artificial neural networks (ANNs), and reinforcement learning (RL). The results of simulation and real-life experimentation have demonstrated that AI-based optimization systems are more efficient compared to the traditional engine control systems in terms of fuel usage, thermal control, and environmental safety.The results of the current study highlight the AI's monumental role in optimizing ICEs, including a reduction in fuel consumption improvement in thermal efficiency, and a significant decrease in harmful emissions. These results are instructive that in the future, AI will play a pivotal role in the development of more efficient, environmentally friendly, and friendly internal combustion engines in keeping up with the rest of the world in reducing environmental footprints and increasing efficiency in energy consumption.

However, several challenges exist to the extensive adoption of AI in ICEs. These impediments include high-quality data, real-time processing, interfaces with old systems, and developing standardized AI models that can generalize to other types of engines and operating environments. Further research, collaboration of AI experts in teams with engineers and regulatory authorities, and investing in new sensor technology and computing hardware on a large scale will meet the challenges.

This paper's recommendations will provide a clear guideline for addressing these problems and allow AI-based optimization frames to be utilized in commercial and industrial engines. AI can be applied to make internal combustion engines more efficient, sustainable, and fit future energy needs, focusing on the trustworthiness of the data used, real-time optimization, cost-effective solutions, and compliance with regulations.

In conclusion, AI-based optimization will be one of the most common sources of innovation in the automotive and industrial industries. As AI technologies continue to evolve, their application in ICEs will be increasingly important in achieving the goals of higher fuel efficiency, reduced emissions, and more efficient engine operation. Future research and development need to refine these AI models and address the current study's problems to unlock AI's full potential in engine optimization.

Future Directions and Recommendations in the area of integration of Artificial Intelligence in Engine Systems.

This study presents various recommendations derived from the found data and challenges to guide future research, industrial design, and the application of Artificial Intelligence (AI) in internal combustion engines (ICEs) and hybrid and electric vehicles (HEVs/EVs).

The major condition that conditions the success of AI-based models is improving the quality and accessibility of data. This will involve creating high precision, high quality, and reliable sensors, creating standardized data collection methods, and encouraging cooperation between researchers and manufacturers. At the same time, the improved performance of real-time processing and the minimization of computational resources also require that low-latency algorithms be designed to run on embedded systems at a low cost by implementing methods like model compression and edge computing.

Secondly, AI models should be standardized and generalized to be flexible in different types of engines, fuel, and climatic conditions.

Multi-task, transfer, and meta-learning can develop adaptable and universal AI structures. Moreover, to reduce the financial and technical cost of retrofitting current systems, a focus should be given to creating modular and simple-to-integrate solutions.

Third, it is necessary to collaborate with regulatory bodies to define unambiguous data management standards, model transparency, and safety measures to provide environmental compliance and innovation. Ethical and safety issues should also be regulated in parallel with the regulatory alignment by creating strict procedures, incorporating redundant fail-safe systems, and implementing explainable AI technologies to increase trust in the decision-making procedures.

Fourth, to achieve ubiquitous implementation, it is crucial to minimize implementation costs, especially in developing economies. This may be done by creating cost-effective AI solutions to preserve performance at the lowest infrastructure changes possible. The emphasis on long-term benefits like fuel savings, decreased compliance costs, or extended engine lifespans will also support initial investments.

Fifth, future studies must be extended to optimize hybrid and electric vehicles. This includes better energy management in hybrid systems by coordinated ICEs and electric motors and better battery operation, charging plans, and battery life in fully electric vehicles. These developments will increase the migration to more sustainable transport systems.

Lastly, increasing awareness and human capacity is essential in improving the adoption rate. Engineer and technician training programs, workshops, pilot projects, and public outreach campaigns will increase trust in AI-driven technologies and their acceptance in the industry and society.

Future Outlook

Introducing AI to internal combustion engines, and later to hybrids and electric vehicles, is a strategic chance that can help achieve greater operational efficiency, higher thermal performance, and significant emissions reductions. By overcoming the challenges of data, computation, costs, and regulation, the industrial sector can make AI a core instrument in creating innovation.

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