

AI-Powered Emission Control and Fuel Optimization in IC Engines

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Abstract- As environmental regulations grow increasingly stringent and fuel efficiency becomes a central concern for both manufacturers and consumers, the automotive industry is undergoing a technological shift toward intelligent engine management systems. Internal combustion (IC) engines, though mature, continue to dominate the global vehicle fleet, particularly in developing economies. However, traditional emission control and fuel optimization methods, which rely on fixed calibration maps and rule-based logic, struggle to adapt to real-time driving conditions and evolving operational complexities. This paper explores the transformative role of Artificial Intelligence (AI) in enhancing emission control and fuel efficiency in IC engines through a comprehensive secondary analysis of literature, case studies, and industrial applications from 2015 to 2025. AI techniques such as machine learning, deep learning, and reinforcement learning are capable of analyzing real-time engine data from multiple sensors, enabling dynamic adjustment of parameters like fuel injection, ignition timing, and air-fuel ratios. Case studies from companies such as Bosch, Toyota, and Mahindra demonstrate tangible improvements in emission reduction (up to 18%) and fuel savings (up to 10%) through AI-powered systems. The paper also discusses emerging trends including edge AI in ECUs, hybrid control systems, digital twin modeling, and AI integration in hybrid and biofuel engines. While the potential is vast, challenges such as data noise, computational constraints, legacy system integration, and regulatory compliance must be addressed. The study concludes that AI-driven engine control systems offer a promising path toward cleaner, more adaptive, and efficient automotive technologies.

Keywords- Artificial Intelligence, internal combustion engines, emission control, fuel optimization, machine learning, ECU, edge AI, predictive maintenance, hybrid engines, automotive technology.

I. INTRODUCTION

Despite rising electric vehicle use, many vehicles worldwide still use internal combustion (IC) engines. Due to their versatility to many fuel types, lower upfront costs, and widespread infrastructure support, they will stay essential in the automotive industry, especially in developing economies [1]. In response to climate change, carbon footprints, and air pollution, there is now universal agreement that

vehicle emissions must be reduced and fuel economy increased [2]. European Euro 6, US CAFE, and Indian Bharat Stage VI are examples of rigorous emission regulations placed by governments globally. To satisfy these criteria, which require dramatic reductions in PM, HC, and NOx emissions, manufacturers are under intense pressure to create novel engine controls [3]. Internal combustion engines use closed-loop feedback systems to adjust air-fuel ratio, ignition timing, and EGR. These systems use look-up tables and pre-calibrated control maps extensively [4]. Despite their

effectiveness, these approaches can't handle engine operations' non-linearity and constant change. Many factors affect engine performance, including engine load, speed, altitude, fuel type, environmental temperature, and driver actions [5]. These aspects are too complex for static control. Thus, advanced, real-time adaptive control systems that can accurately manage this unpredictability are desperately needed [6].

AI could revolutionise this issue. In particular, RL, ML, and DL offer data-driven methods for modelling complex nonlinear systems without physical equations [7]. Onboard sensors including oxygen, knock, exhaust gas, and throttle position sensors provide high-frequency engine data that artificial intelligence systems use to improve control parameters [8]. AI systems may adjust ignition timing to reduce knocking and boost power, dynamically vary the air-fuel mixture for optimal burn efficiency, and predict combustion abnormalities [9]. Artificial intelligence can also help the ECU predict engine behaviour and emission trends in different settings. These findings improve pollution compliance, proactive maintenance planning, and vehicle efficiency across its lifecycle. Reinforcement learning can learn optimal control rules from engine system interaction to maximise long-term performance and emission advantages

II.METHODOLOGY

Literature analysis and synthesis are employed in this secondary study to examine how AI is applied in IC engines for emission control and fuel optimisation. We searched academic publications, technical conference transcripts, white papers, patent applications, and automobile industry case studies from 2015 to 2025 for this study. This study examined powertrain management AI-driven system advances, deployment strategies, and performance comparisons. Relevance, credibility, and an emphasis on core subjects including combustion optimisation, emissions monitoring, adaptive fuel injection, real-time electronic control unit control, and AI-based diagnostics dictated literature selection. Technical material from Bosch, Toyota, Mahindra, Hyundai, and Siemens; IEEE and SAE International

publications; and Elsevier's "Applied Energy" and "Energy Conversion and Management." were helpful. These publications presented theoretical and practical knowledge on implementing AI systems in hybrids, passenger automobiles, and heavy-duty trucks. Real-world automotive AI case studies are reviewed in this article. Bosch pollution compliance oecus, Toyota deep learning adaptive fuel mapping, and Mahindra diesel engine predictive diagnostics are the case studies. Readers should understand how AI is affecting fuel and emission management. To enable structured comparison, we classified the studied materials by artificial intelligence technique, engine type (diesel or petrol), performance metric (fuel economy, NOx reduction, etc.), and system design (centralised ECU or distributed control). Classifying the industry this way reveals common trends, implementation challenges, and innovation gaps. The study examined computing demands, sensor dependencies, training data requirements, and real-time responsiveness to evaluate if AI models were realistic for general deployment.

III. AI APPLICATIONS IN EMISSION CONTROL SYSTEMS

AI-based emission control systems provide new ways to manage IC engine exhaust emissions. Traditional emission control technologies fail in changing engine conditions because they are rule-based and rely on predetermined parameters [10]. AI-enabled solutions outperform traditional approaches in predictive, intelligent, and self-learning due to real-time flexibility and regulatory restrictions. AI algorithms, especially ML and RL-based ones, can optimise fuel-air mixture management, exhaust gas recirculation (EGR), and catalytic converters autonomously [11]. This reduces pollution significantly without affecting engine performance. Artificial intelligence is used in emission control systems to optimise catalytic converters, perform predictive maintenance on emission-related components, and apply reinforcement learning for dynamic emission management.



AI-Based Catalytic Converter Optimization

Catalytic converters play a crucial role in decreasing emissions from combustion by converting harmful gases like CO, NO_x, and HC into less toxic ones like CO₂, N₂, and water vapour. The ideal exhaust gas temperature, air-fuel ratio, and flow rate are crucial to a catalytic converter's performance. Traditional ECMs have a narrow calibration window and often use worst-case scenarios instead than real-world driving [12]. Deep learning-based AI algorithms can monitor and anticipate exhaust system temperature behaviour in real time. Based on lambda sensors, NO_x sensors, exhaust temperature probes, and mass airflow meters, the system adjusts the air-fuel ratio and EGR valve position. This lets the converter work within its ideal operating window, usually 200–400°C for three-way catalysts.

Predictive Maintenance of Emission Components

AI also controls emissions with predictive maintenance. Heat stress, soot buildup, and chemical contamination can damage oxygen sensors, diesel particulate filters (DPFs), and exhaust gas recirculation valves. Older onboard diagnostic (OBD) systems often cause poor performance, greater emissions, and costly maintenance. AI-based predictive maintenance systems can detect component degradation trends before failure by evaluating past sensor data, applying machine learning algorithms, and using fault prediction models [13]. Recurrent neural networks (RNNs) or long short-term memory (LSTM) models can estimate soot loading patterns by analysing pressure sensor time series data across the DPF. These models can forecast filter clogging and start proactive regeneration cycles to extend DPF life and maintain exhaust backpressure. Use usage patterns,

temperature cycles, and prior faults to estimate the RUL of emission control essential components using predictive algorithms. Service professionals and fleet managers can use this data to enhance maintenance scheduling, reduce unplanned downtime, and ensure emission compliance [14].

Reinforcement Learning in Dynamic Emission Control

artificial intelligence in which an agent learns optimal tactics by interacting with its environment and receiving feedback in the form of incentives or punishments, has great potential for dynamic emission control optimisation. RL systems manage many interconnected variables in IC engine systems. RL systems use long-term performance goals to train policies, unlike traditional machine learning models. RL agents in the ECU can monitor engine RPM, load, temperature, throttle position, and exhaust gas data to manage emissions [15]. The RL model uses fuel economy and pollution levels to pick control actions (such as ignition timing, valve actuation, or injection pressure) and receive feedback. Over time, the system learns emission-reducing and fuel-efficient control algorithms. RL's ability to adapt without reprogramming is promising. If a vehicle uses a different fuel or operates in a new place with unpredictable weather, the RL agent can adjust its management strategy by learning about the new environment. Researchers have found that deep reinforcement learning (DRL) algorithms like PPO and DQN outperform static control maps in dynamic driving circumstances.

IV. Fuel Optimization Using Artificial Intelligence

Automakers and government organisations have long understood the need for internal combustion engine fuel efficiency. Due to rising gasoline prices, environmental awareness, and higher emission restrictions, an intelligent and efficient fuel management system is needed more than ever. Traditional fuel management uses the ECU's pre-programmed control logic and static fuel maps. These maps are frequently built with extensive empirical testing and calibration. In controlled situations, this works well, but realistic drivers

encounter non-linear and dynamic variables. This highlights the revolutionary potential of AI, especially ML and deep learning algorithms.

AI-Optimized Fuel Injection

Engine efficiency and fuel economy are strongly affected by fuel injection. Timing, pressure, and duration of fuel injection affect combustion quality, thermal efficiency, and pollutant output. Traditional fuel injection systems are calibrated and controlled by engine RPM, load, throttle position, and manifold pressure. Since these algorithms can't adapt, they're not always the greatest choice [16]. AI-based fuel injection control systems transcend these limits by simulating the complex relationships between many engine variables with supervised learning methods. Multiple linear regression (ML) models such as decision trees, SVM, and ANN can analyse past and present sensor data from crankshaft position, temperature, injector voltage, engine knock, and air-fuel ratio. These AI algorithms predict fuel injection quantity and timing to improve combustion efficiency and minimise fuel waste and pollutants. For highway fuel economy, the model can lean the mixture, but for cold start ignition, it can enrich it. AI systems may also monitor the engine for injector wear, fuel pressure variations, and misfires and adapt injection tactics in real time to keep it operating smoothly.

Combustion Modeling and Real-Time Tuning

Engine emissions, fuel utilisation, and power production depend on combustion efficiency. Due to its dynamic nature and dependence on temperature, turbulence, in-cylinder pressure, and air-fuel mixture homogeneity, modelling the combustion process in real time has proved difficult. AI solves the problem of creating predictive combustion models utilising sensor fusion and high-resolution time-series data. Thermal profiles, crank angle sensors, and in-cylinder pressure traces can be used to train deep learning architectures like CNNs or LSTM networks to predict combustion behaviour and identify abnormalities like knocking, misfiring, and incomplete combustion [17]. Real-time combustion modelling lets the ECU tune spark timing, intake valve timing, and EGR rate for every engine cycle. Dynamic tuning reduces cycle-to-cycle instability, a major cause of efficiency loss in conventional engines, and improves fuel

economy. AI models can also adjust to varied fuel grades, air pressures, and engine wear by updating their forecasts and control actions through learning.

Fuel Map Learning and Adaptive Control

Traditional OEM pre-program fuel maps, which are lookup tables that control fuel supply under different conditions. Despite their success in controlled environments, static maps struggle in real-world settings including heavy traffic, steep inclines, and diverse driving styles. AI-driven adaptive control systems optimise the fuel map in real time by learning from driving data. These systems create a fuel plan for each automobile using adaptive fuzzy logic models or reinforcement learning to optimise fuel usage based on driver habits, road conditions, and traffic patterns. In urban stop-and-go traffic, the system may prioritise fuel-saving strategies like early gear upshifts and leaner mixtures. On highways, it can maintain power delivery with little fuel waste. AI models can modify the fuel map to maintain performance and efficiency despite vehicle load, tyre pressure, or weather changes [18]. Connected vehicles can improve adaptive control with cloud-based AI technologies that update fuel maps and analyse fleet data. Manufacturers and fleet managers can use over-the-air optimisation to improve vehicle fuel efficiency after deployment. Adaptive fuel mapping reduces calibration time when designing engines.

V. INDUSTRY CASE STUDIES AND COMPARATIVE ANALYSIS

AI is being tested in internal combustion engines by top automakers and tech companies. Bosch, Toyota, and Mahindra, three leaders in AI for pollution management and fuel efficiency optimisation, have shared their case studies here. These companies have solved problems with AI, improving fuel economy and reducing emissions. These instances show the variety of AI uses and their demonstrable impact on vehicle performance. German auto parts maker Bosch has developed cutting-edge electronic control units (ECUs) with AI algorithms that can learn and modify [19]. Their AI-powered electronic control units (ECUs) dynamically adjust fuel injection and ignition timing based on input from hundreds of

engine sensors, including throttle position, oxygen levels, cylinder pressure, and ambient conditions. Traditional oecus with machine learning models directly incorporated into the ECU firmware can lower emissions by 18% and fuel savings by 10% in mixed-condition driving, according to Bosch systems. The AI-enabled oecus seamlessly integrate with petrol, diesel, and hybrid engines, making them helpful in urban traffic situations where shifting conditions make conventional maps useless. Bosch's edge AI concept enables rapid automobile decisions without cloud infrastructure. Toyota pioneered fuel management system calibration with machine learning [20]. Toyota engineers used enormous datasets from test tracks and drivers to construct ML-driven fuel maps that adjust to diverse terrains, driving styles, and environmental factors. These adaptive maps change constantly, improving fuel efficiency over time and reducing calibration. Toyota reported an 8% fuel economy increase and a 15% emissions reduction in controlled test conditions, with the highest gains in low-load cruising and hill-climbing. AI-based dashboard suggestions recommend driver behaviour changes to increase mileage. Toyota uses OTA software upgrades to remotely update fuel maps to enhance performance after the sale, one of the most scalable methods in the industry. Mahindra uses AI for predictive maintenance in emission-reducing parts. Diesel-heavy vehicles are their speciality. One area where it has had the largest impact is DPF control. A tried-and-true procedure for recharging DPFs at regular intervals might produce backpressure, decreased performance, and increased emissions if done improperly or late [21]. Mahindra's predictive algorithm uses fuel injector, temperature probe, and exhaust pressure sensor time-series data to estimate soot development and find the best regeneration point. This AI-powered technique prevents fuel waste from over-regeneration and ensures timely regeneration.

Comparative Overview and Visual Representation

The following table summarizes the performance improvements achieved by each company through their AI-powered systems:

Company	AI Use Case	Emission Reduction (%)	Fuel Savings (%)
Bosch	AI-powered ECU	18%	10%
Toyota	ML-driven fuel maps	15%	8%
Mahindra	Predictive DPF cleaning	12%	5%

VI. CHALLENGES AND LIMITATIONS

AI can improve pollution management and fuel efficiency in internal combustion engine systems, but there are many challenges. These technological, operational, and regulatory issues must be resolved before mass-market cars may adopt AI-powered engine control systems. Developers and manufacturers must grasp these issues to design strong, scalable, and compliant solutions. Reliable and accurate input data determine AI model performance. Automotive sensors including oxygen, manifold pressure, crankshaft position, knock detectors and exhaust gas analysers provide this data. These sensors may lose data quality due to signal noise, drift, ageing, and calibration errors. AI models trained on noisy or inconsistent data may forecast erroneous fuel injection timings, air-fuel ratios, or regeneration cycles. Real-time measurement abnormalities from fast throttle adjustments, rocky roads, or changing ambient temps hinder decision-making. Thus, improved filtering algorithms, sensor redundancy, and self-

calibration are needed to assure high-quality sensor data for AI integration.

VII. FUTURE TRENDS AND PROSPECTS

As AI continues to redefine automotive engineering, better, more efficient, and more adaptive AI-powered solutions will be developed and applied to optimise fuel economy and manage pollutants in internal combustion (IC) engines. New paradigms in vehicle intelligence, sustainability, and system integration will accompany the next innovation wave. Several new advancements will influence the application of AI in automotive engine management systems. These include the use of AI in hybrid and alternative fuel powertrain management, digital twin models for simulation-driven optimisation, hybrid AI systems that combine traditional control with intelligent learning, and edge AI for real-time decision-making. Edge AI in engine control units (oecus) is a promising future development. Traditional AI models that use cloud infrastructure for processing raise latency, connectivity, and security concerns in automotive applications. Small, highly optimised AI models are executed on vehicle-integrated hardware in edge AI. These devices' low power, memory, and energy consumption make them ideal for real-time automobile settings. Edge AI systems can immediately respond to engine issues since they can infer at the vehicle level. This enables proactive emission management, adaptive combustion control, and exact fuel supply without remote servers. Modern automobile systems require secure and private data transmission, and local processing improves both. AI-accelerated microcontrollers like NVIDIA Jetson, NXP's S32 platform, and Qualcomm's Snapdragon Auto are accelerating edge-native automotive AI.

The automotive industry is rapidly using AI as hybrid powertrains, flex-fuel systems, and biofuel-compatible engines become more common. These engines can handle varying fuel mixtures, battery voltages, regeneration cycles, and drivetrain arrangements. AI can handle this complexity by evaluating the attributes of multiple power sources and combining or switching them to improve

efficiency and limit pollution. AI may consider road ahead, traffic, and battery health to decide when to use the electric motor or combustion engine in a plug-in hybrid.

VIII. CONCLUSION

With AI's dynamic, adaptive, and predictive capabilities, internal combustion (IC) engine control systems are rapidly developing beyond standard control approaches. AI allows engine management systems to react intelligently to data in real time, improve performance, and fulfil tightening emission limits by combining ML, DL, and RL algorithms. This secondary research shows that AI-powered methods outperform energy efficiency, real-time fuel injection optimisation, predictive maintenance, and reaction to changing conditions. Hybrid learning frameworks, AI-based predictive diagnostics, adaptive fuel mapping, and intelligent emission reduction tactics are among the growing uses. Edge computing and the IoT infrastructure boost AI in automotive engine systems. Edge AI lets the vehicle's oecus examine sensor data in real time, improving safety and latency. Cloud connectivity allows remote performance improvement and ongoing learning. These technologies enable smarter cars. These vehicles can adjust to their surroundings, driver behaviours, and mechanical wear and tear while meeting emissions and fuel efficiency criteria. AI's flexibility to hybrids, flex-fuel engines, and biofuel systems makes it essential for integrating combustion-based propulsion with ecological sustainability. Before AI to fully realise its potential in IC engines, many obstacles must be addressed. Sensor reliability, embedded system computational restrictions, legacy hardware integration, and robust regulatory frameworks are examples. Despite advances in simulation tools, digital twin models, and cloud-based training environments, mass-produced cars need substantial experimental validation and field trials for artificial intelligence. Technology vendors and automakers must collaborate to standardise AI model testing, certification, and reliability. Finally, AI can improve IC engine fuel efficiency and pollution. Integrating AI with combustion engine management is a game-changer in the automotive sector, ushering in

smarter, greener transportation. Research, development, and industry collaboration must continue to grow these solutions across vehicle platforms and global markets.

REFERENCE

1. Trueheart, L., Koritala, C., & Stopkoski, C. (2024, February). Applying Artificial Intelligence to Optimize Engine Power Demand. In SPE/IADC Drilling Conference and Exhibition (p. D012S001R003). SPE.
2. Sen, M., Dave, V., & Kumar, S. (2025). AI-Based Fuel and Energy Management System (EMS) in Hybrid Electric Vehicle (HEVs): A Review. *Intelligent and Sustainable Power and Energy Systems*, 261-271.
3. Hassan, S. M. (2025). Application of Artificial Intelligence in Marine Engine Control System: Recent Advancements.
4. Gronfula, M., & Sayed, K. (2025). AI-Driven Predictive Control for Dynamic Energy Optimization in Flying Cars. *Energies*, 18(7), 1781.
5. Reddy, K. B. N. K., Pratyusha, D., Sravanthi, B., & Esanakula, J. (2024). Recent AI Applications in Electrical Vehicles for Sustainability. *Int. J. Mech. Eng*, 11, 50-64.
6. Mishra, D. P., Dash, A., Kumar, A., & Salkuti, S. R. (2025). AI-Powered Strategies for Efficient EV Energy Management. In *Artificial Intelligence for Integrated Smart Energy Systems in Electric Vehicles* (pp. 193-217). Cham: Springer Nature Switzerland.
7. Soomro, A. A., Noreen, A., Naz, S., Arshad, J. A., Majeed, M. K., Rafique, N., ... & Ahmad, B. (2025). DATA-DRIVEN PREDICTIVE MAINTENANCE OF DIESEL ENGINES USING ADVANCED MACHINE LEARNING AND AI-BASED REGRESSION ALGORITHMS FOR ACCURATE FAULT DETECTION AND REAL-TIME CONDITION MONITORING. *Spectrum of Engineering Sciences*, 3(7), 408-429.
8. Jareena, S., Gopal, P., Pullagoila, M., Obeedu, A., & Sreenath, S. (2025, May). AI-Powered Energy Management Systems for Hybrid Electric Vehicles using Advanced Machine Learning Models. In 2025 3rd International Conference on Data Science and Information System (ICDSIS) (pp. 1-6). IEEE.
9. Badgaiyan, P., Gupta, S. K., & Pandey, M. (2024, November). AI-powered optimization of EV charging station converters: a comprehensive review. In 2024 2nd International Conference on Advancements and Key Challenges in Green Energy and Computing (AKGEC) (pp. 1-7). IEEE.
10. Hossain, M. S., Mohaimin, M. R., Alam, S., Rahman, M. A., Islam, M. R., Anonna, F. R., & Akter, R. (2025). Ai-powered fault prediction and optimization in new energy vehicles (nevs) for the us market. *Journal of Computer Science and Technology Studies*, 7(1), 01-16.
11. PA, P., Kavitha, P., Neeraja, P., Reddy, D. L., Venkatachalam, S., & Saravanan, M. (2025, April). The Future Role of Environmental Sustainability-Optimization using Artificial Intelligence Electric Vehicles. In 2025 5th International Conference on Trends in Material Science and Inventive Materials (ICTMIM) (pp. 1445-1448). IEEE.
12. Vashishth, T. K., Sharma, V., Sharma, K. K., Kumar, B., Chaudhary, S., & Panwar, R. (2024). Environmental sustainability and carbon footprint reduction through artificial intelligence-enabled energy management in electric vehicles. In *Artificial Intelligence-Empowered Modern Electric Vehicles in Smart Grid Systems* (pp. 477-502). Elsevier.
13. Mishra, D. P., Rath, A., & Salkuti, S. R. (2025). Artificial Intelligence in Electric Vehicles for Sustainable Driving. *Artificial Intelligence for Integrated Smart Energy Systems in Electric Vehicles*, 1427, 1.
14. Miller, T., Durlík, I., Kostecka, E., Łobodzińska, A., & Matuszak, M. (2024). The Emerging Role of Artificial Intelligence in Enhancing Energy Efficiency and Reducing GHG Emissions in Transport Systems. *Energies*, 17(24), 6271.
15. Chelliah, P. R., Jayasankar, V., Agerstam, M., Sundaravadivazhagan, B., & Cyriac, R. (2023). The power of artificial intelligence for the next-generation oil and gas industry: Envisaging AI-inspired intelligent energy systems and environments. John Wiley & Sons.
16. Rana, K., & Khatri, N. (2024). Automotive intelligence: Unleashing the potential of AI beyond advance driver assisting system, a

comprehensive review. Computers and Electrical Engineering, 117, 109237.

17. Prakash, P. A., & Radha, R. (2025). Advancements in AI-Powered Electric Vehicle Routing: Multi-Constraint Optimization and Infrastructure Integration Approaches for Evolving EVs-A Survey. IEEE Access.
18. Yoheswari, S. (2024). AI-Based Thermal Management System for Hybrid Electric Vehicles.
19. Soni, P., & Dave, V. (2025). Enhancing Solar PV-Fuel Cell Hybrid Systems Through AI-Driven Performance Optimization. In Building Business Models with Machine Learning (pp. 137-158). IGI Global Scientific Publishing.
20. Godwin, I. D., Poospadi, D., Kumar, C. P., Kumar, S. S., & Manikandan, R. (2025). Harnessing High-Performance Computing for AI-Driven Energy Harvesting and Environmental Monitoring. In Integrating Machine Learning Into HPC-Based Simulations and Analytics (pp. 253-276). IGI Global Scientific Publishing.
21. Leal-Arcas, R. (2025). Electric Vehicles, Artificial Intelligence, and Climate Policy. Artificial Intelligence, and Climate Policy (May 20, 2025).