SSRG International Journal of Electrical and Electronics Engineering
ISSN: 2348-8379/ https://doi.org/10.14445/23488379/IJEEE-V12I10P116

Volume 12 Issue 10, 217-231, October 2025

Review Article

A Comprehensive Research Review on Adaptive Fuel Injection System with AI Optimized Fuel Delivery for Trucks

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Received: 11 August 2025 Revised: 14 September 2025 Accepted: 16 October 2025 Published: 30 October 2025

Abstract *- Artificial Intelligence (AI) is reforming the fuel injection in heavy-duty trucks by empowering the precise, adaptive control of fuel injection, timing, and air-fuel proportions. This paper reviews the recent progress in the AI-driven adaptive fuel injection, which mainly focuses on the algorithmic outlooks, the incorporation of sensors, and control tactics. While existing studies have proclaimed the substantial gains in fuel effectiveness and minimization of emissions, most of them remained confined to offline analysis, particular fuel varieties, and regulated environments with nominal large-scale real-world authentication. This review has assembled the preceding research by the machine learning methodology, differentiates performance metrics, and ascertains the gap related to computational effectiveness, cross-fuel versatility, and integration with IoT-empowered engine control units. Opportunities for the betterment that comprises lightweight real-time frameworks, reinforcement learning for ceaseless adaptation, economic and regulatory architectures to reinforce scalable placement in the next-generation transportation systems.*

Keywords *- Intelligent Fuel Optimization, Adaptive Engine Control, AI-Driven Fuel Efficiency, Predictive Fuel Injection, Smart Vehicle Powertrain.*

1. Introduction

Advancements in the heavy-duty fuel injection systems have been observed to affect trucks tremendously. Furthermore, that was to magnify engine performance, improving fuel efficiency, and emission reduction. Primarily, primitive fuel was passed on by mechanical fuel injection systems. Supply lacked the precision that is essential to an ideal burning, leading to impracticability and exceeding pollutant release. The metamorphosis to Electronic Fuel Injection (EFI) systems has capacitated more factual control of fuel-air rates, improved combustion efficiency, and overall engine power [1].

The Artificial Intelligence (AI) synthesis into fuel injection systems in modern years has become a transformative strategy. Through preaching machine learning algorithms and real-time sensor information, AI will be able to continuously reform the fuel insertion timing, volume of injection, and air-fuel ratios based on different driving states, driver behaviour, and environmental elements [4]. This flexibility is highly beneficial for heavy-duty trucks, which have to face broad deviations in the loads, geography, and weather during operation. The new AI systems have combined the high-end sensors, such as temperature, oxygen, throttle position, vehicle load sensors, and engine speed sensors, with the anticipatory analytics in such a way that they push the fuel economy, emissions, and proactive maintenance [2]. Irrespective of these developments, the resulting predicaments have been shunned. Most AI-based retrievals work as offline analytical implementations instead of real-time adaptive systems that are assimilated into the onboard ECUs [9]. Ongoing enforcements that often upgrade for specific fuel kinds under controlled laboratory circumstances, with bounded capacity to acclimatize dynamically to composite fuels or transitioning driving atmospheres [3]. Real-world arrangements are further impeded by the high analytical requirements of several AI models, the omission of standardized structures for coordinating IoT sensor data with ECU control, and the shortage of large-scale field endorsement across varied truck fleets [5]. Various available reviews that have discussed individual algorithms, different types of fuels, or regulated states in the laboratory, such as work, uniquely compile AI-controlled adaptive fuel injection calls to action between multiple machine learning archetypes, placing emphasis on real-time, self-learning capabilities related to a wide variety of fuels and operating conditions [6]. It also presents a systematic classification of the previously researched works in the category of types of algorithms, deepened comparison tables, and the possibility of large-scale application, providing a complete source of information to the researcher and industrial specialist [7].

This paper has provided a brief about the identified gaps by handing over an inclusive review of AI-streamlined adaptive fuel injection systems for heavy-duty trucks. It has surveyed the state of modern methodologies, resolved technological and operational curbs, and featured the opportunities for prospering lightweight, self-learning architectures that are adept at real-time fuel interjection, rising under volatile conditions. This review endeavours to guide future exploration towards the practical, expandable solutions that boost efficacy, reduce emissions, and secure long-term viability in the transportation sector [8].

The paper conducts a comprehensive literature review on the topic of AI-optimized adaptive fuel injection in heavy-duty trucks. Section 2 has laid the foundations of AI confederation within the fuel injection systems. In Section 3, the control methods and fuel infusion optimization algorithms have been presented. In Section 4, the current studies in AI-based fuel injection have been fully analysed. Section 5 highlights the areas of research that are more significant and involve further research and inquisition, whereas Section 6 concludes with the final developments in the field. Ultimately, additional subsections have predetermined the destiny, opportunities, and rejection of progressive next-generation intelligent delivery systems of fuels.

2. Requisites of Adaptive Fuel Injection Systems

The proposed adaptive fuel injection system based on AI-optimized fuel delivery will improve fuel efficiency in heavy-duty trucks by taking advantage of artificial intelligence and real-time sensor data. It is a system that charismatically adapts. Fuel injection ranges depending on the driving requirements, variation in load, and engine execution values. The methodology suggested is that of federation of an AI-powered Engine Control Unit (ECU) that will process the data provided by various sensors in order to enhance fuel provision, optimize emissions, and recalibrate engine operation. Figure 1 is the perfect representation of the graphical perspective of the AI-Optimized Fuel Injection System, and the methodology is the conventionalized approach that is related to real-time data acquisition, AI-based decision making, and accurate control of fuel injection.

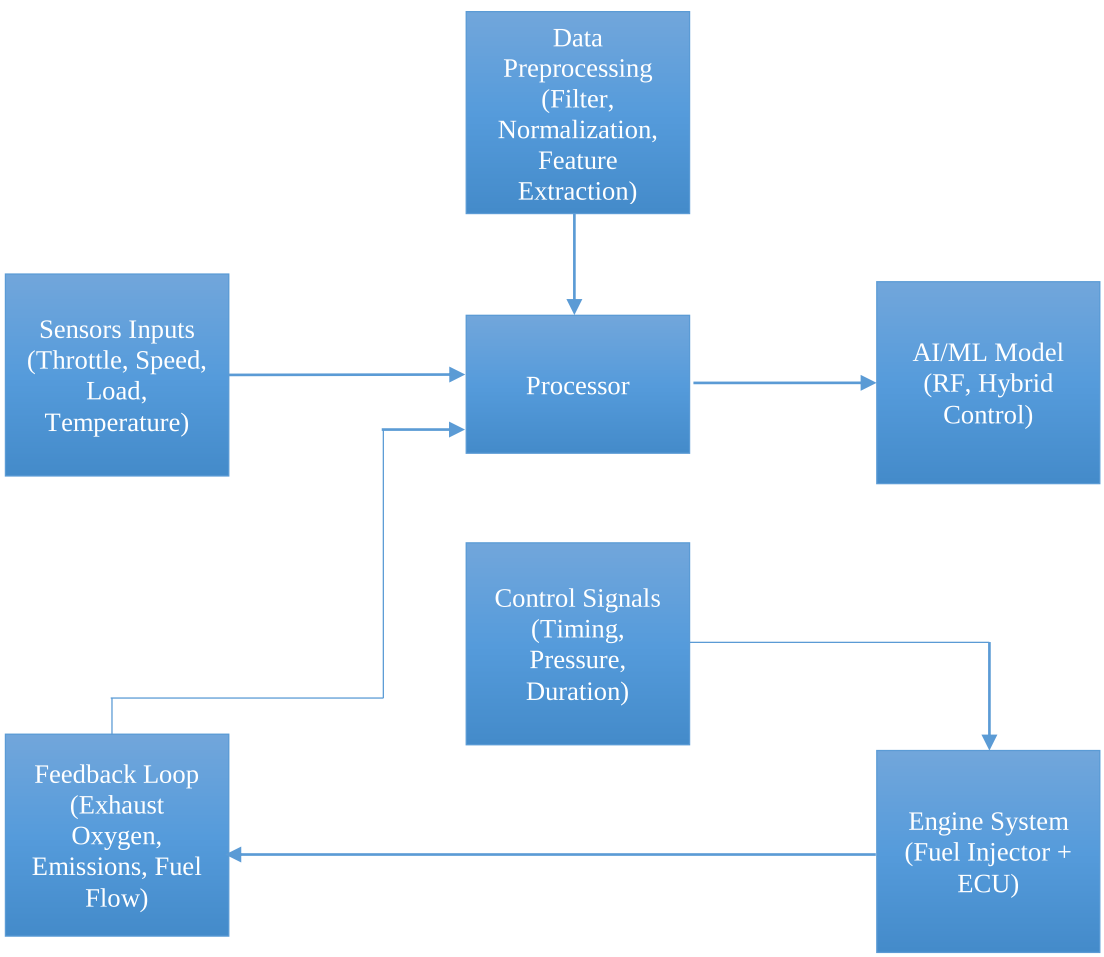

Fig. 1 Block diagram for adaptive fuel injection system

2.1. Sensor Inputs and Data Acquisition

The AI-based ECU relies on the various sensors to collect information that is crucial in optimizing the fuel injection process. These sensors constantly observe divergent parameters, so that the fuel consignment system balances automatically to discrete operating cases. The load sensors are climax types of sensors that are used to identify the deviations of the load in the truck. The increased loads require more power and, hence, require more fuel injection, but the lighter loads would run effectively with the fuel abated. Such sensors introduce real-time to the ECU, giving it the ability to change the amount of fuel.

The speed of the engine, or Revolution Per Minute (RPM) sensor, monitors the rate of rotation of the engine. This approach is necessary when the optimum fuel injection rate is to be determined so that it is possible to create efficient combustion and prevent the waste of fuel. The terrain sensor monitors the character of the driving surface, such as slopes, plummet, and rough street conditions. Trucks climbing the hills demand more fuel to overcome gravitational refusal, and on descents, the shipment of fuel may be held in check to save energy. The ECU determines the terrain information and adjusts the fuel injection that is activated to achieve the maximum.

An AI-powered fuel injection system is equipped with a temperature sensor that monitors the engine temperature and other environmental temperatures continuously so as to control the delivery of fuel in an appropriate manner. It transmits live data to the AI-operated ECU that modulates the fuel-air mixture depending on the thermal engine conditions. When the engine starts cold, the ECU raises the volume of fuel injected to ensure a suitable combustion, and when overheating occurs, the injection is terminated to avoid damaging the engine. AI algorithms are analyzed to override trends and external factors in a dynamic way to promote fuel competencies. The temperature sensor assists in conforming to load and terrain sensors in order to give adaptive fuel injections to promote the performance of the engine, fuel economy, and gross durability of the trucks. Exhaust Gas Oxygen controls the pulses of the oxygen concentration in exhaust gases, allocating life-sustaining response based on the capacity to burn. When excess oxygen is detected, that indicates that there is a fine mixture, and the low oxygen level favours a rich mixture. Such feedback grants the air-fuel ratio to the ECU to provide full combustion and nominal emissions.

2.2. AI-Enabled ECU and Decision-Making Process

The adaptive fuel injection system contains the nucleus of the AI-enabled ECU, which is liable to compose sensor data and develop real-time choices. The artificial intelligence algorithm within the ECU does analyses using machine learning modes and certified and real-time information to enable speculative changes on the fuel injection. The decision course that is in the ECU has the following steps:

2.2.1. Data Processing

ECU still receives the information from load sensors, RPM sensors, terrain sensors, temperature sensors, and oxygen sensors. The data is crude and preprogrammed to remove noise and aberration.

2.2.2. Pattern Recognition and Learning

ECU employs machine learning algorithms to determine the patterns of the ingestion of fuel, with such types of driving conditions as regression models, Support Vector Machines (SVM), and neural networks.

2.2.3. Predictive Fuel Optimization

The AI model anticipates the forced fuel injection level by anticipating the trends of the previous and current data. It swiftly alters the injector timing and injector quantity to correct the actual time demand of the engine.

2.2.4. Feedback Mechanism

The Oxygen sensor is a continuous check in terms of the productivity of combustion. The ECU will adjust the fuel injection rates when the inefficiencies are identified so that the air-fuel ratio has the archetypal values.

2.3. Fuel Injection Control Process

Once the ECU controlled by AI meets the criteria for maximum fuel injection, direct control signals are sent to the Fuel Injector Control Actuator. It is an actuator that injects the fuel into the Combustion Chamber and certifies it to be burning of fuel that is efficient. The operation is as convoys:

2.3.1. Injector Timing Control

ECU also assumes the rightful fuel injection three times, depending on the engine speed, load, temperature, and conditions of the terrain. Timing results in complete combustion improvement, which is favourable in comparison with fuel economy.

2.3.2. Fuel Quantity Control

ECU measures the ideal size of fuel required to be burned. It ensures that the engine does not unnecessarily receive excess fuel, which will spill over emissions, or poor fuel reception will cause loss of power.

2.3.3. Dynamic Adjustments

ECU is continuously changed in accordance with the scheme of fuel injection as the driving plights change. In order to prevent unexpected acceleration, the system enhances fuel injection to allow the system to raise scrimp fuel power clamours, but when coasting, it decreases delivery of fuel to scrimp fuel.

The AI-oriented fuel inoculation procedure is represented as a system model where the processor, i.e., ECU/AI controller, is acting as a central node. It unites sensor inputs, preprocessing units, and AI/ML archetypes to give rise to streamlined signals for controlling the engine system. There is a resulting feedback loop of emissions and feat data sent back into the processor, which triggers constant acclimatization and closed-loop regulation of the implantation plan.

3. Literature Survey

AI and Machine Learning have been progressively applied to improve fuel interpolation and related procedures in heavy-duty vehicles, aiming to improve the fuel capability, scale down the emissions, and activate adaptive control. The reviewed studies span a range of methods, datasets, and application conditions. Table 1 presents a comparative recapitulation of 30 key analyses, encompassing methods, performance metrics, datasets, findings, and limitations. Figure 2 presents a visual representation of system usage in the literature.

3.1. Neural Network Approaches

Wong et al. [1] came up with a provably sound neural-network virtual sensor to estimate quantities of fuel injection under adversarial sensor scenarios. The article has demonstrated that traditional NNs experience catastrophic performance hitches when sensor noise is put into play (performance error increasing by single numbers baselines to approximately 43.8% in adversarial conditions). Wong et al. minimized the worst-case relative error down to around 10.69% using robustness verification and robustness-conscious training and noted 3% error using clean data. Its contribution is two-fold: it proves the guarantee of formal robustness to a virtual fuel-sensor model that can be applied to ECUs, and it reports training and assessment practices when under a systematically perturbed noise. The authors indicated that key limitations are required on-vehicle validation and that provable-robustness techniques of embedded ECU deployment are computationally expensive.

Rogoz et al. [4] used a Multi-Layer Perceptron (MLP) to forecast the fuel consumption of vehicles using a data set of 1,750 cars. Fidelity of their MLP was very high - Pearson correlation in the range of 0.93-0.95, and R2 values were greater than 0.98, which implied that the model well reflects the nonlinear relationship between vehicle/operational parameters and fuel consumption in passenger car data. Sensitivity analysis and error quantification are included in the study, demonstrating the possibility of MLPs generalizing under the condition of having enough representative data. Limitations: Domain transfer of the models that are trained on passenger-car data might not easily extend to heavy-duty truck dynamics without further, truck-specific telematics data.

Mandal et al. [17]. The feedforward ANN models are applied to predict the performance and emissions of Compression Ignition (CI) engines in a dual-fuel (diesel-biogas) mode by Mandal et al. ANN is trained on the data from the engine testbench, which implies a strong correlation with the experimental results on the brake thermal efficiency and the index of emissions. The paper discussed the capability of ANNs to model complex interactions in combustion that are brought about by alternative fuels, as well as marking the requirement of solid experimental design and sufficient training sets to avoid overfitting. Next-step engineering issues include practical deployment issues, which include computational cost and the requirement to maintain constant retraining to respond to fuel variability.

Katreddi & Thiruvengadam [26] used ANN modelling on trip-based telematics of modern heavy-duty trucks and forecast fuel consumption in the real driving environment. On-road inputs such as engine load, speed, vehicle speed, duty cycles, and their ANN are shown to be better than other competing ML methods on the same data, showing ANN to be suitable in trip-level fuel forecasting when sufficient telematics data are available. The article has highlighted the resilience of models to heterogeneous driving characteristics but indicated that further data to cover all fleets in different locations must be included, and that on-board inference would still have to compress the models to fit ECU requirements.

Do et al. [29] gave a comparative analysis of several ML models, which include ANN, ANFIS, GRNN, RBFN, and SVR, in predicting engine performance and NOx emissions in the case of biodiesel blends, which are of B0, B10, and B20. Although SVR provided the best overall predictive performance in their experiments, ANNs, including MLP variants, have provided competitive results, especially when bigger training sets or more elaborate feature sets are applied. The article responsibly recorded RMSE/R2/MAE values of each model and explained that the ranking of models is highly sensitive to the size of the dataset, noise, and the object of prediction, meaning performance vs. emissions. Practical weaknesses observed will be the lack of real-world validation and the computational complexity of certain versions of ANN to control injections in real-time.

3.2. Support Vector Machine (SVM) Methods

Rahul [2] presented the regression, Support Vector Machines (SVM/SVR), and Model Predictive Control (MPC) techniques in their survey, which have been synthesized to apply fuel-efficiency optimization to automotive systems. The review lists real-life case studies of SVMs in robust prediction of moderate-sized datasets and the capability of SVM to extrapolate using small samples. The article highlighted the strengths of SVM, which include regularization and flexibility of the kernel, but also highlighted, as a limitation in practice, the impossibility of continuous online learning and adaptation with a standard SVM implementation, which can be a problem with embedded, adaptive ECU control.

Kishore et al. [15] surveyed methods of AI applied to monitor the fuel-cell, and the SVMs are listed among the effective classifiers/regressors in the situation of fault detection and state-estimation. They described how SVMs and hybrid SVM schemes can offer credible classification using relatively small training sets and gave an overview of the types of input features that are being used, which are voltage/current signatures and temperature/humidity. The implications of the study are practical; SVMs have appeal in resource-limited diagnostic modules; however, they need feature engineering and meticulous cross-validation. In addition, SVMs do not offer a simple means to continual learning or changing operating profiles.

3.3. Regression-Based Approaches

Shateri et al. [3] compared various regression and ML models, such as NNs, Random Forest Regression, and Gaussian Process Regression, to predict the consumption of diesel fuel. GPR has higher predictive accuracy and principled uncertainty estimates on its exploratory diesel-engine datasets than the alternatives. This paper has highlighted the appropriateness of GPR when it is important to quantify the uncertainty, e.g., safety/diagnostics, and presented the effect of kernel selection and hyperparameter optimization on the outcomes. The authors cited the limitations of the computational scaling of GPR on very large data sets, but suggest sparse approximations, or local GPR instances, to be used in embedded systems.

Kaleli et al. [19] used Genetic Algorithm (GA) optimization and Gaussian Process Regression to optimize and design an electromechanical EGR cooling system. The GPR model has forecasted the existence of links between the EGR ratio/exhaust temperature and target outputs (NOx, BSFC). Bench tests with GA as a parameter searcher on top of the regression surrogate made large gains in NOx and Brake Specific Fuel Consumption (BSFC). The contribution showed the effectiveness of regression in the control-parameter optimization and highlighted the interpretability of GPR; the weaknesses of the method encompassed the use of controlled experimental data and the necessity to confirm the predictions of a surrogate in full-vehicle experiments.

Lee et al. [30] used simple linear regression models to establish 3-D spray topology of Gasoline Direct-Injection (GDI) systems under a variety of fuels and ambient conditions. Their linear surrogate is highly accurate, and most importantly, the computational cost is significantly reduced compared to that of full CFD simulations. It rendered linear and low-order regression appealing as a surrogate model in design loops or to be utilized in quicker model-based controllers. The paper, however, observed a drawback when it comes to highly nonlinear regimes, for e.g., flash boiling or transient multi-hole injectors, etc., and additional higher fidelity or customized local models are needed.

3.4. Ensemble Learning Methods

Gong et al. [18] evaluated several predictive models such as logistic regression, back-propagation neural network, decision tree, and Random Forest for fuel consumption prediction of heavy-duty diesel trucks using 21 influencing factors, which are engine state, road characteristics, weather, etc. Using a dataset of 34 HDDTs, Random Forest outperformed competing models, showed robustness to feature noise, and offered interpretable variable importance measures. The study has advocated RF for on-fleet fuel prognosis and highlighted the method's resilience across heterogeneous operating conditions; it cautions that model fidelity depends on the quality and representativeness of collected telematics.

Pavithra et al. [13] presented a cloud-connected engine management prototype using Gradient Boosting Machines (GBM) to optimize combustion parameters such as spark timing and air-fuel ratio. By offloading heavy computation to cloud backends and applying GBM, the system can iteratively refine parameter maps and demonstrate reductions in fuel consumption and emissions in test setups. This work illustrated ensembles' power when paired with cloud resources, but the authors discussed latency, data privacy, and connectivity trade-offs that limit direct closed-loop ECU control.

Park et al. [23] developed a lightweight NOx prediction model using Random Forest with SHAP explainability and Pearson correlation-based feature selection. They reduced the model's input set to 11 key features while maintaining parity with more complex baselines in prediction accuracy. The result is a practical, explainable ensemble suitable for low-input, near-real-time monitoring and prospective on-vehicle use. The study highlighted a deployment pathway: feature reduction plus explainability can make ensembles feasible for embedded contexts.

Karunamurthy et al. [27] applied a Random Forest regressor trained on a modest dataset (≈324 samples) to predict performance and emissions in a dual-fuel (biogas and diesel) engine. The RF model, coupled with Lagrangian optimization, identified operating points that improved performance while reducing emissions. The work emphasized ensembles' capability to deliver strong predictions with limited data and to guide optimization, but also notes statistical limitations from small sample sizes that call for further validation.

Sanjeevannavar et al. [25] employed multiple ensemble and tree-based methods for the prediction and optimization of IC-engine performance and emissions. Their sustainability article documents method comparison, including boosting techniques, and demonstrates how ensemble approaches provide consistent, high-accuracy estimates for BTE and emission indices across experimental data. The paper suggested ensemble models as strong candidates for supporting engine calibration and rapid prototyping; it also discussed the need for compression/pruning strategies if ensembles are to be moved on-board.

3.5. Hybrid and Neuro-Fuzzy Models

Veza et al. [7] compared ELMAN and Cascade Neural Networks (ENN and CNN) with an Adaptive Neuro-Fuzzy Inference System (ANFIS) to predict important fuel properties of Acetone-Butanol-Ethanol (ABE)-diesel mixtures (calorific value, density, viscosity). Their findings revealed that ANFIS gives the best predictions with the lowest error, which indicated the benefit of neuro-fuzzy systems in integrating human-understandable fuzzy rules and data-based parameter estimation. The paper has emphasized the interpretability of ANFIS in fuel property modelling; however, it indicates that dynamic injection control cannot be extended without linking these property surrogates to combustion level models.

Sharma P [5] used Gene Expression Programming (GEP) to predict the performance of the diesel engine and its emissions when using biodiesel blends made of linseed oil. GEP models have high R2(0.9854-0.9998) when predicting brake thermal efficiency, fuel consumption, and emissions with the engine test data. The symbolic models offered small interpretable formulae that can be incorporated into model-based controllers or applied to sensitivity studies. There are limitations, such as the fact that GEP is only based on representative experimental data and may be brittle outside of where it is trained to operate.

Khan et al. [24] explored RCCI combustion using mixtures of CNG and algal biodiesel. They used hybrid ML ensemble regressors and regularized linear models like LASSO to model the outputs and emissions of the combustion at different CNG energy fractions. Their combination approach gave them high predictive accuracy and feature selection through LASSO to set the influential operating parameters. Some of the reported results have included a better thermal performance and less NOx/smoke at certain blend ratios. The research proved that hybrid pipelines ensembled and sparse linear models can provide accurate predictions as well as interpretable parameter information to optimize fuel blending.

3.6. Other AI and Data-Driven Approaches

Wu et al. [22] presented a high-fidelity deep-learning surrogate of turbulent combustion, based on autoregressive structures with novel training strategies, unbent training, noise injection to enhance the robustness of the model, and long-term spatiotemporal extrapolation. Their surrogate has been proven to extrapolate to new scenarios with a high level of reliability on 2 turbulent-combustion datasets and using fewer computing resources than a naive deep model. The applicability of the work to the field of fuel-injection control is that it supports the development of digital twins and the fast training of controllers. The constraints of the work are that training is prohibitively expensive to compute and that transferring surrogate knowledge to lightweight ECUs is required. Wen et al. [20] used the Gradient Boosting Regression (GBR) as one of the models to make predictions of NOx and CO_2 emissions in light diesel vehicles under realistic driving conditions, which are urban, suburban, and highway. The paper highlighted the importance of analysis of feature-importance, i.e., the identification of the mass air flow and exhaust flow as the most significant, and proved that the ability to select the features carefully will lead to a significant improvement in the reliability of the model. Wen et al. note the trade-offs among the complexity and generalizability of models in the prediction of real-road emissions.

Ferrara et al. [14] examined the energy management approaches in heavy-duty fuel-cell cars based on real-world samples of driving approximately 1,750 hours. The heuristic, model-based, and predictive schemes are compared, and it is concluded that the predictive model-based / ML-assisted schemes can be used to enhance the hydrogen economy and system lifetime. This system-level exercise highlights the usage of ML strategies with more vehicle energy management and the significance of longer duration and realistic datasets to validate the strategy.

Ihme et al. [16] offered an extensive survey of machine learning in combustion studies, defining the concepts, recent developments, and future opportunities (interpretability, data scarcity, physics integration). The review summarizes the application of ML between subscale experiments on the one hand and engine-scale surrogates on the other hand, and proposes hybrid physics-ML models that can enhance the credibility of control activities.

Fayyazi et al. [6] overviewed the use of AI/ML in energy management, the control and optimization of hydrogen fuel-cell vehicles. They reported ML-driven controllers that allowed predicting the control, real-time control, and V2X integration better, and identified particular aspects of system-level design, such as state estimation and health monitoring, that should be considered to deploy it in heavy-duty transport successfully.

Rao et al. [10] proposed an IoT-based smart e-fuel station prototype with ESP32 hardware to automate fuel level, cloud data transmission, RFID-based payment, and reordering. The system is proven as a proof-of-concept to enhance the efficiency of operations and reduce their dependence on manual interventions, which can serve as an example of the IoT and ML to optimize the fuel logistics instead of direct injection control; however, it is applicable to the fleet fuel-management ecosystems. Pereira et al. [21] developed a non-invasive sensor and datalogger system on construction trucks, which consists of specific sensors and ML algorithms to forecast the fuel usage. The work displayed an enhanced accuracy of estimation and revealed the importance of specific sensor arrays and wireless telemetry on the real-time monitoring and after-training of models. Limitations include the generalization of models outside the classes of construction vehicles.

Li et al. [8] included the discussion of cold-start performance in a diesel engine with the development of an environment-adaptive intake-air preheating control strategy. They used optical experiments and bench tests with the help of thermodynamic modelling to obtain adaptive preheat maps that vary according to ambient temperature, altitude, and engine speed in order to enhance ignition and lower cold-start emissions. The paper has provided the practical control charts, which may be integrated with ML-issued ECUs to manage cold-starts in a more effective manner; the shortcoming is that maps are designed to fit particular engine geometries and might need to be specially tailored to each engine family.

Altosole et al. [11] examined a hybrid turbocharger design for the marine dual-fuel engines that complements the role of turbocharging to enhance energy conversion efficiency over the load ranges with the help of electrically generated power. Experimental and simulation comparisons showed better flexibility and fuel economy. Even though the turbocharger presented is marine, the hybrid turbocharger lessons are applicable to powertrain architecture decisions in which variable fuelling and electric assist exist.

Paramasivam et al. [12]. The hybrid decision-making method, Fuzzy Analytical Hierarchy Process (FAHP) and Gray Relational Analysis (GRA), with experiments of Aegle Marmelos bio-oil biofuels and nano-additives CuO, graphene, are used in this piece of work to select the best biofuel options for diesel engines. The paper also presented a particular combination (AC15G15) that provides the most reasonable trade-off between performance and emissions, indicating how multi-criteria decision formulas and additive engineering contribute to fuel-sensitive controller design.

Wargula et al. [9] discussed the emissions of small spark-ignition engines with non-commercial fuel supply systems. Their experimental results have demonstrated the trade-offs in emissions, i.e., a decrease in CO, CO2, and HC can be accompanied by an increase in NOx when the system varies under certain conditions, and the complexity and conflicting requirements among these objectives, and the need to use multi-objective measures on the controllers.

Chacko et al. [28] discussed the increase of cetane number in biodiesel blends (B20) with partial hydrogenation and 2-Ethylhexyl Nitrate (EHN) additive. According to bench tests with different loads, partial hydrogenation exhibits better combustion gains, particularly in the mid loads, than EHN, which means that there is an easy way to enhance ignition and minimize harmful emissions. This paper presented the experimental coefficients and directions applicable in tuning AI controllers that need fuel chemistry to be considered.

Table 1. Summary of extant works

Author	Application	ML/AI Method	Dataset	Evaluation Metrics	Key findings	Limitations
Wong et al. [1]	Amount of Fuel injection using virtual sensors	Empirically robust Neural Network	Engine sensor data with hostile/noise conditions	Mean Relative Error ~ 10.69% in pivotal range; ~ 3% on immaculate data	Resilient NN resists sensor noise and ameliorates virtual sensor accuracy	Focused on sturdiness, real-truck placement is not stated
Rahul. [2]	Fuel proficiency optimization (Overview + Cases)	Regression, SVM, MPC (Survey/ Cases)	Real-world different case studies	Review	AI refines fuel management over rule-based command	Principally review; bounded quantitative criteria
Shateri et al. [3]	Fuel expenditure anticipation	NN, Random Forest Regression, and Gaussian Process Regression	Exploratory diesel engine data	GPR finest accuracy	GPR is preferable for fuel usage prediction	Exhaustive metric standards are not mentioned
Rogoz et al. [4]	Vehicle fuel consumption for passenger cars	ANN (MLP)	1750 vehicle records	Pearson 0.93-0.95; $R^2 > 0.98$	MLP confirmed high portending accuracy	Passenger-Directed towards the car
Sharma P. [5]	Performance / Emissions with Biodiesel mixes	Gene Expression Programming (GEP)	Engine tests/ Patterned data	$R^2 = 0.9854$-0.9998	GEP unerringly predicts BTE, fuel avail, and emissions	Focused upon Substitute-fuel, not infusion control perse

Fayyazi et al. [6]	Energy supervision for hydrogen fuel cell vehicles	AI/ML grounded intelligent controllers (Review/Applications)	Real-world heavy-duty data	Not Applicable-Review	Data-impelled controllers strengthen prediction/control	Not explicit to injection systems
Veza et al. [7]	Envisioning ABE fuel properties of ABE-diesel blends	AI paragons like ENN, CNN, and ANFIS were developed and compared	Lab fuel-property data	ANFIS negligible errors	ANFIS made the most meticulous predictions	Pursued on properties; Meandering to injection control
Li et al. [8]	Cold start intake air foreheating execution in diesel engines	Environment-resilient control (model-based)	Analysis & thermodynamic outlining	Cold-start performance betterment.	Pliant preheat map tweaks the cold-start functionality.	Model-based; not ML-heavy
Wargula et al. [9]	Small SI engine emissions vs non-commercial fuel arrangements	Analogous testing	Bench tests	Emissions include HC, CO, NOx, and fuel depletion.	Accentuates emissions trade-offs astride systems	Small engines; exterior heavy-duty diesel
Rao et al. [10]	Smart e-fuel station employing IoT	IoT system, not ML	Prototype enactment	System serviceability that involves automation/monitoring.	Mechanized fuel monitoring/operations	Injection intended
Altosole et al. [11]	Turbocharging methods in marine dual-fuel engines	Acquainted with a hybrid turbocharger that devises electric power to enhance energy exertion	Marine engine tests	Fuel potency & energy transmutation efficiency	Improved fuel productivity, affordability, and overall energy metamorphosis	Marine framework
Paramasivam et al. [12]	Optimizing biofuel integration for better engine fulfillment	FAHP and GRA mean multi-criteria	Engine tests with nano-additives	BTE, BSFC, emissions	Comprehended the AC15G15 blend as the finest for modernized performance and curtailed emissions	Fuel conception focused
Pavithra et al. [13]	Engine management along the cloud network	Availed cloud-connected technologies and Gradient Boosting Machines (GBM)	Cloud and engine data	Fuel salvage %, emission diminuation %	Amended engine performance while dwindling fuel expenditure and emissions	Spark-ignition prominence
Ferrara et al. [14]	Efficient energy handling is crucial for fuel cell vehicles, especially in heavy-duty transportation	Assessed heuristic, model-based, and augmented strategies implementing real-world driving data	1750 real-world driving, fluctuating loads	H_2 uptake, system durability	Predictive scenarios improved hydrogen frugality and system firmness	Concentrated on the fuel cell

Kishore et al. [15]	Fuel cells prognostics	NN, GA, SVM (review/applications)	Diagnostics datasets	Analytical classification veracity.	AI has empowered accurate and swift fault investigation with minimal data assemblage.	Absorbed in diagnostics; not injection governing
Ihme et al. [16]	Vast combustion data from simulations and sensors necessitate advanced dissection methods.	Disinterred ML techniques for data-driven acumen in combustion indagation	Simulations, experiments, and sensors	Not Applicable	Improved inquiry, prediction, and capability in combustion-akin studies	Review paper
Mandal et al. [17]	CI engines with biogas (dual-fuel)	ANN	Engine experiments	High interdependence between ANN and undertakings	Biogas is feasible with meticulous ANN predictions	Alternative fuel; not injection timing regulation
Gong et al. [18]	HDDT fuel consumption prediction (21 factors)	Appropriated logistic regression and ML models to pursue fuel consumption influences, with random forest functioning best	Factual data from 34 HDDTs	RF gives the highest exactitude	RF is best for the HDDT fuel use conjecture.	Exact metrics are not reported.
Kaleli et al. [19]	Electromechanical EGR cooling maximization	Gaussian Process Regression and GA	Engine tests	Enacted significant reductions in NOx emissions and BSFC, bettering engine competence	GPR is compelling for EGR/BSFC trade-offs	Not direct infusion control
Wen et al. [20]	To dissect the impact of input attributes on NOx and CO2 emission conjectures	Gradient Boosting Regression (GBR) model	Real-road urban, suburban, and highway data	High precision; key facets MAF & exhaust flow	The feature set acutely impacts authenticity	Potent dependence on feature caliber and limited to one road-state dataset, hindering generalizability.
Pereira et al. [21]	Fuel usage in heavy construction trucks	Machine Learning, where the algorithm is vague here	Devoted sensors and a datalogger	Reformed estimation factuality reported; no definitive RMSE/R^2 values presumed.	Sensor and ML rectifies fuel reckoning; IoT-aptness	Algorithm and benchmarks are not stipulated; focused only on construction trucks, circumscribing platitude to on-road

						heavy-duty vehicles
Wu et al. [22]	Delegated turbulent combustion forecasting	Deep learning based high allegiance model with novel training modes like unbowed training and noise injection	High-constancy combustion datasets	Vigorously long-term chrono spatial forecasts	Bettered firmness via training schemes	Substitute modeling; not on-vehicle
Park et al. [23]	Lightweight NOx projection	Effectuated the random forest method with SHAP feature selection	Diesel engine dataset	11-feature model, similar to base model certainty	Authentic NOx with low input intricacy	Not instantly fuel extent control
Khan et al. [24]	Recovering CI engine conveyance and reducing emissions by executing a blend of microalgae biodiesel and CNG in RCCI combustion	ML models such as GBR and LASSO regression	Engine experiments on diverse CNG shares	Realized 4.35% higher thermal efficiency with 30% CNG while mitigating NOx and smoke emissions	ML predicts blend effects	Combustion mode, not injection handling
Kumar et al. [25]	To presage engine performance	ML models, including XG Boost, RF, DT, and LR	Engine data	Not reported	ML foretells & streamlines engine outputs	Results are limited to engine test data without wider validation
Katreddi et al. [26]	Croaking fuel consumption in heavy-duty trucks under real-world particulars	ANN, where the method was compared with other models	On-road telematics such as engine load, speed, etc.	ANN outclassed other ML methods, facilitating accurate and orderly fuel refining	Practical implementation for rapid advancement	The model is trained on region-distinct driving data; high reliance on immense on-road datasets limits scalability and relevance.
Karunamurthy et al. [27]	Adumbrating performance and emissions in a dual-fuel engine chartering biogas and diesel	Random Forest Regressor and Lagrangian optimization	324 provisional points	Portent accuracy is stated using regression metrics such as R^2, RMSE; definite values are not designated.	RF prophecies outputs; perfected inputs are detected	Inadequate dataset size

Chacko et al. [28]	Augmenting the cetane number of a diesel-biodiesel (B20) amalgamate for better combustion superiority	Accustomed to partial hydrogenation and 2-Ethylhexyl nitrate (EHN) extension to enhance ignition properties	Engine tests at erratic loads	Prediction exactness is reported by regression metrics, which include R^2, RMSE, and MAE.	Biased hydrogenation outstrips EHN at mid-load	Corroborated only the lab requirements with limited biodiesel blends; needs on-road confirmation and real-time deployment inquiry
Do et al. [29]	Portending engine gratification and NOx emissions for biodiesel commingles	Paralleled multiple ML models such as ANN, ANFIS, GRNN, RBFN, and SVR	Engine tests with B0, B10 and B20	SVR is best in total	SVR is considered exceptional among associated models	Cramped to biodiesel blends and constrained datasets; falls short of real-world validation and real-time realization feasibility
Lee et al. [30]	Meticulous prediction of 3D spray and air-fuel intermixing in GDI engines	Expanded an ML algorithm endowing a linear regression model to beforehand 3D spray topology under assorted conditions	Spray diagnostics datasets	Enacted high exactness in spray diagnostics, outshining CFD methods	Uncomplicated model forbodes 3D spray underneath varied situations	Vindicated only on controlled spray test instances; absence of engine/real-world substantiation and real-time control assimilation

Table 1 provides a condensed summary of thirty recent studies on AI-driven adaptive fuel injection systems, presenting the main findings of these studies, evaluation metrics, and limitations. A similar pattern has shed light on the way various machines have been enlightened learning algorithms, ANN, RF, SVM, and hybrid methods are run on the basis of different experimental conditions and fuel varieties. This discussion has led to a brainstorming of studies that surround neural networks and ensemble techniques. The reinforcement learning and lightweight real-time models were unexplored. Through a combination of approaches with their specific results and hindrances, Table 1 presents a clear view of the common research prospect. This review develops the existing literature by offering a synthesized and comparative locus of this work. This is in contrast to the past inspections that did not give much importance to the particular algorithms, fuel type, or minor case studies; the paper splits the knowledge of thirty recent papers that were achieved through a machine learning paradigm and established in various speculative settings. The calm provisional table contributed to the facilitation of the composition to better the insights into the relative capacity and drawbacks of offbeat strategies. Emphasizing the unexplored fields of reinforcement training, massive on-the-road climbing, IoT-certified ECU incorporation, and economic probability, the review not only synthesizes existing knowledge but also creates a benchmark of future studies and practical implementation.

4. Research Gap

Machine Learning (ML) and AI-based predictive models experienced significant improvements in the field of fuel injection optimization of heavy-duty trucks. In any case, consequential loopholes exist in the fulfillment of a completely adaptive, real-time AI-optimized fuel injection system that improves fuel efficiency, shaves off emissions, and closes long-term viability. On this basis, the leading gaps in the research established are:

- Prevailing research predominantly focuses on contemplating fuel consumption on average rather than dynamically reconciling fuel injection constants based on real-time conditions.
- AI models are mainly used for post-facto interpretation rather than live, on-board AI-assisted fuel transit adjustments. A self-learning model that incessantly adapts to alternates in terrain, vehicle load, driving sequences, and environmental plights has yet to flourish.
- Extant studies acquire sensor data for overseeing engine performance but flounder to integrate real-time IoT sensor data into an AI-based adaptive control system for fuel injection. The bridle of edge computing and cloud-based AI models for real-time injection control remains unfathomable.
- There is no regimented framework for the coherent interaction between AI, IoT sensors, and electronic control units for adaptive fuel injection.
- Research has focused on optimizing explicit fuel types such as diesel, biodiesel, CNG, or hydrogen-enhanced fuels, but there is no AI model capable of tailoring fuel injection schemes dynamically based on fuel sort and blend concord. There is no AI-controlled hybrid fuel injection system that can flexibly switch ancillary fuel sources to amplify efficiency and assuage emissions.
- Most studies are conducted in controlled laboratory milieus, and the AI models that emerged are not commercially tested in real-world trucking predicaments such as variable road inclines, temperature extremes, altitude deviations, and urban versus highway driving. Continuing AI systems are not proficient in fluid fuel injection with regard to external driving determinants.
- Although a few of the studies have imposed temporary AI-influenced fuel clairvoyance, no long-term AI schema that acquires experience on chronic fuel injection schemes to reorganize future ways has been utilized.
- A research gap that is condemnatory is the lack of an AI system that is based on reinforcement learning to self-rebuild fuel delivery over time. The existing machine learning algorithms fail to absorb previous driving records to pursue the trend in order to make fuel injection vigorous.
- Algorithms Myriad AI models have found application in fuel capacity research, which are algorithmically costly, in ways that make their use impractical in real-time, on-board pursuit in truck ECUs.
- Lightweight AI models capable of spurring on embedded are needed for car-based processors that do not need the rigorous premium computing capability. The current models of training ML-based speculations are trained on frozen datasets, when a perfect system in AI learning should be capable of perpetual learning and adaptation when applied to real-world hypotheses.
- The heavy-duty trucks operate in a variety of conditions, including the highways of long distances, the stop-and-go urban operation, off-road positions, and mountainous areas, but the models of fuel injection driven by AI lack the flexibility to address these mutations.
- Uttermost AI-based fuel streamlining models have been tested on small datasets or single vehicle archetypes, with minimal real-world corroboration on commercial truck fleets.
- AI trials are insufficient in real trucking efforts under varying driving conditions and payload silhouettes. The absence of large-scale real-time AI fostering limits the suitability to benchmark AI models for indubitable fuel efficiency dividends.

5. State-of-the-Art in Prevailing Research

This section glorifies the current research undertaken towards the AI-driven Fuel Injection System architecture. The quantitative data for state-of-the-art studies in the prevailing study are extracted from standard publications such as IEEE, Springer, and Elsevier, which include “Adaptive Fuel Injection System” as a keyword. Tables 2, 3, and 4 express the numerical details of published scripts in IEEE, Elsevier, and Springer accordingly (cited on 18-March-2024 (India 3:45 pm).

Table 2. Numerical details from IEEE

Type of Publications (IEEE)	Total Counts
Conferences	40
Journals & Magazines	35
Early Access Articles	23
Standards	20
Books	15
Courses	10

Table 3. Numerical details from Springer

Type of Publications (Springer)	Total Counts
Series	35
Journals & Magazines	30
Web Pages	27
Books	11

Table 4. Numerical details from Elsevier

Type of Publications (Elsevier)	Total Counts
Web Pages	45
Journals & Magazines	32
Books	15

The percentage-wise assessment of publication sources has accentuated the distribution of research outcomes across the publishers. Springer has featured 100% depiction in series, 62.5% in web pages, and 30.92% in journals and magazines. IEEE has prevailed with 100% compass in courses, standards, easy-access articles, and conferences, besides with 36.58% in books and 36.08% in journals and articles. Elsevier rationalizes for 37.5% of web pages, 36.58% of books, and 32.98% of journals and magazines, which is moderately lower than IEEE and Springer. Figure 2 below identifies the fact that the majority of benefaction to AI-based fuel insinuation research has been refereed on IEEE and Springer platforms, with a rather minor role played by Elsevier.

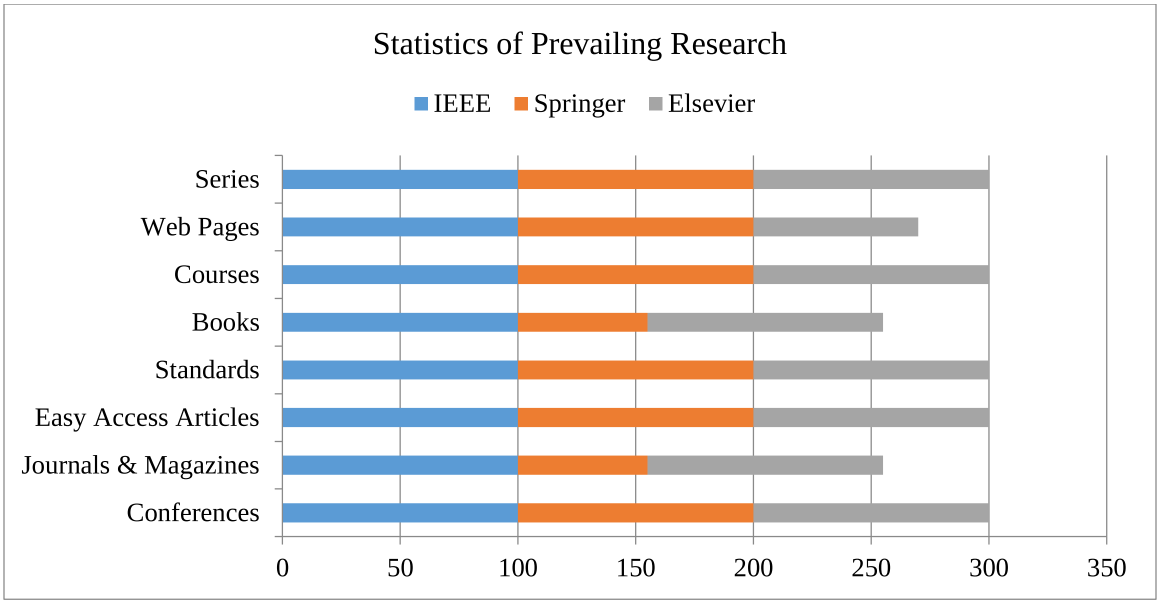

Fig. 2 Analysis of the prevailing research trends

6. Economic and Cost Analysis

The AI-driven compliant fuel implantation systems are strongly associated with the economic credibility of their latency to minimise fuel consumption and enhance the functional performance of heavy-duty cars. Research indicates that injecting timing and pressure through AI may produce fuel means of 5-12 that would result in significant cost savings among fleet operators in the long-term project. Other comforts include long engine life because mechanical distress and service needs are reduced. However, the primary action of inventing and funding luxury sensors, ECUs, and artificial intelligence-driven software remains a barrier to the carefree adoption. The fuel and subsistence long-term holdings must be traded off with the short-term costs of integration, which leads to a cost-availability trade-off. A large fleet deployment makes economies of scale play their part, and the technology becomes successively cheaper as it is used.

7. Practical Aspects of Implementation and Scaling

When it comes to the development of AI-based fuel injection programs, it is necessary to pay close attention to the compatibility of the hardware with it, real-time processing capabilities, and system stability. The problem with newfangled machine learning models involves incorporating these models into the existing ECUs, which involves statistical efficiency and a low-weight algorithm framework to guarantee real-time docility in the presence of controlled driving plights. Real-life crises are replete with soothing roughness in responding to sensor noise, erratic fuel quality, and contradictory operating conditions such as high altitude or hot temperatures. These systems should also be measured against mercantile fleets by regimented communication standards to ECUs that are ready to be interconnected with the IoT, software updates that are free of errors, and compatibility with legacy systems. OEMs, AI monitors, and fleet drivers are bound to communicate with one another in order to translate the laboratory development results into a possible large-scale mobilization.

8. Ethical and Regulatory Considerations

Another factor that raises serious principled and regulatory issues is the delegation of AI-based fuel interpolation systems. Such systems, which may be considered as supervisory in character, must meet with rigid emission regimes such as Euro VI and Bharat Stage VI, which incorporate open and testable control rationale to realize a permit for the market application. Ethical issues are concerned with the ethical use of the vehicle telematics data, and it is concluded that confidential, workable, and location-specific data obtained on the sensors are guarded against garbage or privacy invasion. On the same note, AI in the determination of verdicts should be justifiable and accountable, particularly when infusion strategies affect emissions and the health effects on individuals. It is necessary to alleviate these concerns by concentrating on the observable regulatory environments, moral AI training, and procedural testing procedures, enriching trust and accelerating approval.

9. Future Scope and Research Directions

Reinforcement Learning (RL) offers a good line of work for developing this work. Unlike the supervised or regression-based models whose Parkinson centrality is founded on the prepared datasets, RL enables systems to acquire the most appropriate actions by continuously interacting with the environment. This devotes the controller to dynamically acclimate injection timing, pressure, and fullness during non-periodic load requirements, topography, and the merits of fuels. In long-haul trucks, when driving patterns and working atmosphere are very unpredictable, RL suggests a special skill in real-time fuel and emission maximization.

The forthcoming research should pose the question of incorporating the RL algorithms in ECUs and lightweight and computationally capable architectures that are good enough to be implemented in-road. Combining RL with digital twins and high-constancy engine simulators would speed up training and reduce the significance of risks of explicit vehicle trial, and also, training of entire trucking fleets can be enabled by scouting multi-agent RL systems, and they can play off common exposures to reduce performance and flexibility. The next-generation fuel transportation systems of the heavy-duty transportation can redefine with the capacity to bridge flexible learning and heavy control through reinforcement learning.

10. Conclusion

This review has consolidated the knowledge of thirty new studies in the field of AI-based adaptive fuel injection systems, presented a well-organized comparison of the machine learning techniques, level of valuation, and limitations. Although neural networks and ensemble techniques have been mostly written about in active research, the reinforcement learning, lightweight real-time models, and large-scale on-road substantiation were also immaculate. This is relevant to the novelty of the work, which integrates in its combined approach of combining the technical advances with the economic investigation, barriers to implementation, and ethical and regulatory considerations, which expands beyond antecedent reviews, which were mostly enfolded in algorithms. Future research needs to emphasize the learnings of reinforcement, digital twins, and fleet-level acclimatization, as well as control cost-efficacy and adherence to emission regulations. By capturing the two modern advantages and irrepressible intervals, this review provides a roadmap on how to advance the next-generation insightful fuel injection systems that are formal, sustainable, and designed to be adopted by industries. By encapsulating both contemporary strengths and insistent gaps, this review provides a roadmap for progressing the next-generation insightful fuel injection systems that are methodical, sustainable, and primed for industrial acquisition.

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