Review of Artificial Intelligent Algorithms for Engine Performance, Control, and Diagnosis

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Abstract: This paper reviews the artificial intelligent algorithms in engine management. This study provides a clear image of the current state of affairs for the past 15 years and provides fresh insights and improvements for future directions in the field of engine management. The scope of this paper comprises three main aspects to be discussed, namely, engine performance, engine control, and engine diagnosis. The first is associated with the need to control the basic characteristics that prove that the engine is working properly, namely, emission control and fuel economy. Engine control refers to the ability to identify and fulfill the requirements derived from performance, emissions, and durability. In this part, hybrid electric vehicle (HEV) application and transient operations are discussed. Lastly, engine diagnosis entails assessment techniques that can be used to identify problems in the engine and solve them accordingly. In this part, misfire detection, knock detection, and intake system leakage will be evaluated. In engine performance, neural network algorithms provide efficient results in terms of emission control and fuel economy as the requirements are easily achievable. However, when it comes to engine control and diagnosis, the fuzzy logic rule with its strong robustness and neural networks algorithms are limited in efficiency due to the complex nature of the processes and the presence of big data, for instance, in HEVs in engine control. That has brought forward the usage of reinforcement learning and novel machine learning algorithms in recent years to maximize efficiency in engine control and engine diagnosis, as highlighted in the following part. The PRISMA methodology was used to justify the reference selection in this review.

Keywords: internal combustion engine; artificial intelligence algorithm; engine performance; engine control; engine diagnosis

1. Introduction

1.1. Scope of the Paper

A review of artificial intelligent algorithms for engine performance, control, and diagnosis is the focus of this paper. In addition to that, recommendations for future work in the field are provided. Artificial intelligence (AI) composed of machine learning algorithms and deep learning algorithms, is intelligence demonstrated by machines, as opposed to the natural intelligence displayed by animals and humans. AI also refers to any system that perceives its environment and takes actions that maximize its chance of achieving its goals or objectives.

We have obligations to foresee, control, and plan accordingly to ensure that nothing goes wrong throughout the entire process of engine operation for the smooth functioning of the engine, as performance and environmental criteria have continued to climb over time. The global increase in vehicle-related pollutants highlights the necessity of efficient internal combustion engines (ICEs). Between 2000 and 2030, India, China, The United States, and the European Union are expected to add almost 630 million automobiles to their fleets [1]. Between 2000 and 2030, transportation-related emissions will increase by more than 85 percent. However, increases in fuel efficiency that reduce CO₂ emissions by 1.5 to 2.5 Gt by 2050 appear to be feasible.
AI is a promising strategy that is being used to address a variety of issues, such as engineering [2], medicine [3], information technology [4], and many other applications [5–8]. When there are a lot of inputs, outputs, or decision scenarios, AI technology is a powerful tool for modeling complicated systems with nonlinear input–output relationships [9]. In the same manner, as with many other data-driven approaches, artificial intelligent models are constructed without a physical understanding of the system [10,11], yet the majority of them can nevertheless predict physical occurrences if they are properly trained and if sufficient training data is available [12,13].

1.2. Why the Choice of Artificial Intelligent Algorithms in Engines?

After the first and second waves of artificial intelligent algorithms development in the 1970s and 2000s, respectively, we are currently in the midst of a third wave [14]. There were always conventional ways for engine operations to be performed, but there were many challenges that contributed to the development of artificial intelligent algorithms to solve those issues. It is challenging to anticipate, regulate, and optimize the extremely nonlinear and complex phenomena that occur inside an ICE using conventional methods, including, but not limited to, 2D and 3D mapping of basic engine characteristics. Examples of phenomena that occur inside the engine include a large number of homes–kinetic nonlinear reactions that take place in steady state and transient ICE operations; in-cylinder temperature and pressure gradients; multi-phase fluid interactions; formation of particulate matters and gaseous emission; and many more.

Furthermore, artificial intelligent algorithms provide more powerful control models because of a significant difficulty that has not been fully addressed by conventional ICE management systems, namely, regulating stochastic cyclic variability in various ICE combustion modes, such as homogeneous charge compression ignition (HCCI) or reactivity regulated compression ignition (RCCI). These past years have seen a rapid rise in big data. In other words, we can obtain a large amount of information and countless details from the engine in terms of speed, indicated torque, fuel injection, pressure, load, fuel consumption, temperature, and many others. The best way to handle the enormous amount of data and use it to the maximum extent is through the use of artificial intelligent algorithms in terms of significantly increasing efficiency while, consequently reducing the time, errors, cost, and effort in engine management. In addition, as stated in [15], AI technology helps in the development of effective, precise, and real-time peer-to-peer learning approaches to track performance, gather/process data, and learn from a significant number of comparable ICEs connected to a network.

2. Body
2.1. Artificial Intelligence (AI) Algorithms in Engine Performance

Engine performance generally refers to how efficiently an engine supplies usable energy compared to some other comparable engines or how well it produces power (output) concerning energy input. Engine operating behavior in the speed–load domain, such as the behavior of emissions, fuel consumption, noise, mechanical loading, and thermal loading, is frequently used to describe engine performance.

2.1.1. AI algorithms in Emission Control

The government seeks to control the amount of toxic pollutants, such as carbon monoxide (CO) and nitric oxide (NOx), by legislation. The high-temperature combustion process produces emissions, which can be reduced by modifying engine operating settings. Global demand for automobiles has increased as a result of the rising population. Periodically, worries about the pollution that an engine emits keep growing. Engine operation has recently been forced into regimes that are constrained by combustion instabilities, as engine control systems have advanced in recent years in a continuous effort to increase efficiency and decrease emissions. The unfavorable anomalous combustion events that these instabilities cause make it difficult to further increase engine efficiency. Reactive control techniques
and conventional, purely physics-based, models have trouble simulating many of the relevant phenomena. Techniques utilizing artificial intelligence (AI) have some promise for improving combustion stability control.

Genetic Algorithms in Emission Control

It is an undisputed fact that public transit buses are the most common mode of transportation for the general public. The study as shown in Figure 1 demonstrated the use of a neuro-fuzzy model to forecast the emissions produced by real transit vehicles running on biodiesel. The data generation process was carried out utilizing the cutting-edge “portable emissions measurement system.” The neuro-fuzzy approaches are quite competent in handling data noise, which is required in the case of any potential overfitting. The Adaptive Neuro-Fuzzy Inference System (ANFIS) and the Dynamic Evolving Neuro-Fuzzy Inference System (DENFIS) are the two neuro-fuzzy methods employed in this investigation, although the ANFIS model displayed more accuracy in terms of the entire study. The contaminants that this article is examining are Nox, HC, CO, CO$_2$, and PM. The two fuels that were utilized, B10 and B20, are studied. Various studies have shown that the switch to biodiesel from diesel reduces HC, CO, CO$_2$, and PM, but contributes to a rise in Nox emissions. Five models were developed to obtain forecasts for each of the five different categories of emissions since ANFIS only provided one result. For Nox and CO$_2$, the ANFIS model’s predictions were remarkably accurate.

![Flowchart](image)

**Figure 1.** Optimization of ANFIS model when implemented with GA.

Neural Networks (NN and ANN) Algorithms in Emission Control

Neural networks are mathematical representations of how the brain learns and stores information. Since neural networks are applied to machines, they are referred to as “artificial neural networks” as a whole. Numerous crucial input variables that directly affect the emissions of the engine were taken into consideration during the investigation as can be seen in Figure 2. Included in the output variables were CO, CO$_2$, HC, and Nox. Virtual...
sensors are used when advanced artificial intelligence approaches are used. The predictions made were based on numbers.

Figure 2. Basic working principle of the proposed algorithm.

In addition, Ghobadian B. et al. [16] developed an artificial neural network model to forecast engine emissions, brake power, and torque as the main outputs. The prototype was tested using a diesel engine that ran on biodiesel made from used vegetable frying oil. By using this process, a sizable amount of data was generated, aiding the ANN model in self-training. The findings after the results were created and tested demonstrated that the back-propagation method was sufficient for providing precise forecasts of engine torque, brake power, and emissions. The computed mean squared error was 0.0004, which is quite low and approaching the optimal value.

To forecast the performance and emissions of diesel engines, Dharma S. et al. [17] performed ANN modeling on biodiesel based on jatropha. A back-propagation approach was used to implement the ANN model. ANN demonstrated a 98% coefficient of determination (R2) value, proving its accuracy yet again. Brake thermal efficiency, brake power, and exhaust emissions were the variables analyzed.

Conclusion: It is evident from the statistical data in Figure 3 below that artificial neural networks are frequently utilized in engine emissions prediction modeling. This has created fresh opportunities for study into finding ever-more-optimal algorithms and cutting-edge methods to improve the accuracy of the outcomes. Artificial neural networks provide satisfactory results in emission control, as highlighted above.

Data Representing Use of Various Models

Figure 3. Statistical data representation of frequently used AI modeling techniques.

2.1.2. AI Algorithms in Fuel Consumption

The automotive industry is currently very concerned about vehicle fuel consumption, and one of the primary objectives of automotive engineering is to reduce a vehicle’s fuel consumption. To increase a vehicle’s fuel efficiency, automakers change several of its
primary design elements. Various models are used (both machine learning and purely analytical), taking into account the vehicle’s velocity, acceleration, forces that resist movement, and other parameters that allow accurate estimation of the vehicle’s fuel consumption. Much work goes into predicting the instantaneous fuel consumption of vehicles [18–20].

For assessing the fuel efficiency of automobiles using simulation-based models and data-driven models, several studies have already been presented. To predict fuel consumption, a simulation model was created based on engine capacity, fuel injection, fuel specification, aerodynamic drag, grade resistance, rolling resistance, and atmospheric conditions.

To predict vehicle emissions and fuel consumption, a statistical model that is quick and easy to use in comparison to the physical load-based approach was created. After examining the effects of road infrastructure [21], traffic [22], drivers’ actions [23], weather [24,25], and ambient temperature on fuel consumption, it was found that eco-driving influences can cut fuel consumption by 10%. The advent of big data and artificial intelligence has made it possible for businesses to model enormous volumes of data to save emissions and fuel use. Artificial neural networks (ANN), support vector machines (SVM), random forests (RF), and others are machine learning approaches that are frequently used to address complicated issues. These methods have been used to calculate the emissions and fuel usage of cars, lorries, ships, and airplanes [26–29].

SVM, RF, and ANN algorithms were employed by the authors in [27] for the goal of predicting fuel consumption. The ANN and SVM algorithms were effective, however, the RF algorithm fared better than either of them. SVM, RF, and ANN each had coefficients of determination (R2) that are 0.83, 0.87, and 0.85, respectively.

The authors discussed identifying concerns with driving styles in [30]. The K-means clustering technique was employed to distinguish between various driving styles. Three sorts of driving behaviors are recognized: normal, delicate, and aggressive categories. Additionally, they made use of neural networks, support vector machines, random forests, and K-nearest neighbor models. When trucks were carrying a big load, random forest’s overall accuracy was 95.39 percent; when they were not, it is 90.74 percent. The most fuel was consumed and 10% more was used when driving aggressively than when driving normally.

Ref. [31] employed the Boruta algorithm (BA) and the neural networks (NNs) algorithm to calculate the fuel consumption of a large fleet of vehicles traveling on various pavement types. Comparing the results of BA to earlier research that employed the same data, BA produced positive results. For test data, the created NN algorithm had an (R2) value of 0.88. NN, which showed it to be a viable option for efficiently evaluating huge datasets and forecasting how road roughness and macrotexture affect truck fuel consumption.

Neural Networks (NN) Algorithms in Fuel Consumption

An extremely powerful computer model called an artificial neural network is used to estimate and approximate complex, unknown functions and systems. The biological nervous systems that serve as the inspiration for neural networks are typically represented as layers of neurons. Since artificial neural networks can learn intricate nonlinear mappings between the system’s inputs and outputs, they are employed to solve complex issues.

Ref. [31] used time series inputs for vehicle velocity, acceleration, and road slope to predict fuel consumption. For this, a variety of data-driven models were taken into consideration, including ones based on neural networks and linear regression.

Based on GPS- and CAN-based tracking data captured on many city buses during their routine operation, the suggested prediction algorithms were parameterized and evaluated as shown in Figure 4. The test results show that the neural network-based approach is suited for a variety of applications since it offers good prediction accuracy and tolerable execution speed [32].
vehicle dynamics, powertrain characteristics, and multi-dimensional maps are typically not predictable fuel consumption. For this, a variety of data-driven models were taken into consideration, including ones based on neural networks and linear regression.

The approach is suited for a variety of applications since it offers good prediction accuracy and tolerable execution speed [32]. The test results show that the neural network-based approach had been used in another related research project to forecast fuel consumption, using a limited training dataset, but the outcomes were not good enough. The R-squared value from its model was 0.004624. Only the RPM TPS-based equation was necessary. However, in this study, both the VS MAF-based equation and the RPM TPS-based equation were employed. The outcomes of this investigation demonstrated in Figure 5 were superior to those of the other contenders, who used the SVM to apply the RPM TPS-based equation, as their R-squared/R^2 equals: 0.004624 while implementing their RPM_TPS-based equation [34].

Support Vector Machine (SVM) Algorithm in Fuel Prediction

The support vector machine (SVM) algorithm is one of the most well-known machine learning algorithms. A specific value or a group of classes can be predicted using the SVM method in either classification or regression form. It has been applied in numerous studies involving the forecasting of fuel consumption.

Ref. [33] used SVM to suggest an ML model for predicting fuel use. The SVM approach had been used in another related research project to forecast fuel consumption using a limited training dataset, but the outcomes were not good enough. The R-squared value from its model was 0.004624. Only the RPM TPS-based equation was necessary. However, in this study, both the VS MAF-based equation and the RPM TPS-based equation were employed.

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Conclusion: In general, there are two main categories of fuel consumption models: first-principle (physics-based) models, which describe the dynamics of a vehicle at each time step using a set of mathematical equations corresponding to various vehicle subsystems and components, and (ii) data-driven machine learning (ML) models, which represent an abstract mapping of a set of input/explanatory variables into an output space defined by a target variable (s). High prediction accuracy can be achieved using physics-based techniques, albeit at the expense of poor computational efficiency. The fact that various vehicle dynamics, powertrain characteristics, and multi-dimensional maps are typically not available is another drawback of physics-based models. Therefore, it is necessary to create a quick, macroscopic model that can anticipate fuel consumption for a whole driving cycle.
Conclusion: In general, there are two main categories of fuel consumption models:

- Artificial neural networks (NNs) are the most often utilized models for these applications because they are global approximators that can represent the nonlinear properties of a complex system by utilizing a nonlinear activation function. In contrast to physical models, the NNs are also easily re-parameterized for different kinds of vehicles and give better results. Figure 6 below highlights the rise in the influence of AI models in the last 10–15 years.

![Image of AI models usage in engine prediction over the last decade.](image)

**Figure 6.** The progress of AI models usage in engine prediction over the last decade.

### 2.2. Artificial Intelligence (AI) Algorithms in Engine Control

Engine control refers to any system which is part of the engine type design that controls, limits, or monitors engine operation, and is necessary for the continued airworthiness of the engine. Today’s technological advancements have demonstrated the power of artificial intelligence (AI)-based control algorithms and their positive impact on the environment. In an engine control unit, resulting inaccuracies in the function output can lead to additional fuel consumption, drivability deficiencies, and, in the worst case, engine damage.

#### 2.2.1. AI Algorithms in HEV Control

Surprisingly, the idea of a hybrid electric car predates the automobile itself. However, the main goal was to help the ICE function at an acceptable level, not so much to reduce fuel consumption [35]. Nowadays, the world is facing problems of resource shortages and environmental pollution. With the continuous production of automobiles, accelerating urbanization, air pollution caused by vehicle emissions, and the large amount of oil consumption of traditional vehicles, the transformation of traditional vehicles becomes a problem that must be solved immediately. Countries are vigorously developing new energy vehicles. In long run, the research on pure electric vehicles is bound to be the main technical direction of new energy vehicles. From traditional energy vehicles to pure electric vehicles, the research of hybrid vehicles is the transition route. Although hybrid electric vehicles will be replaced by pure electric vehicles, the significance of hybrid electric vehicles should not be underestimated. It is a necessary research process and transition. HEVs consisting of an internal combustion engine (ICE) and electric motor(s) (EM) have the potential of improving fuel economy by operating the ICE in the optimum efficiency range and by making use of regenerative braking during deceleration. Moreover, they show improvements in emissions with minimum extra cost.

The hybrid powertrain’s fuel-saving principle is simple to understand. According to this theory, the HEV often transitions between several operating modes, after which the electro-mechanical energy is converted into a hybrid powertrain. The key to creating an
effective HEV as demonstrated in Figure 7 is the energy management strategy (EMS), which is integrated into the vehicle controller and controls the energy flows in the hybrid engine. This “energy management” refers to the design of advanced control logic to determine the appropriate energy and power flow among the engine, motor, and battery. The function of EMS is to maximize the efficiency of the whole system [36].

![Diagram of Parallel HEV](image)

**Figure 7.** Powertrain architecture of a typical parallel HEV.

Heuristic techniques and optimization-based tactics can be used to categorize EMS. The key benefits of heuristic techniques are strong robustness and real-time performance, which rely on a set of rules to provide the control command. The category is divided into two primary sections as can be seen in Figure 8 below: rule-based techniques and fuzzy logic approaches. Optimization-based strategies, such as dynamic programming (DP), genetic algorithm (GA), model predictive control (MPC), and equivalent consumption minimization strategy, rely on analytical or numerical optimization algorithms to give control commands per system models. Heuristic techniques typically perform worse economically than actual strategies. More meaningful information can be gathered thanks to the advancement of sensor and information technologies, and numerous new EMS types have been created based on cutting-edge innovations such as the global positioning system, cloud computing, and game theory. Additionally, the technologies behind intelligent vehicles (IV) and intelligent transportation systems (ITS), which are now trending, enable HEVs to perform even better economically [37].

**Neural Network Algorithm in Speed Control of HEV**

Neural networks are effective pattern recognition tools that include collections because of their exceptional capacity to extract meaning from complex or ambiguous data of identical mathematical models by simulating biological nerve systems. ANNs have demonstrated their ability to recognize intricate nonlinear systems and are well suited for creating intricate internal mapping from inputs to control actions by seeing trends that are too intricate for either humans or other computer techniques to pick up on. The static-type neural network controller has shortened the development process and simplified control implementation. In [35], a feedforward artificial neural network controller with three layers was built as shown in Figure 9. Weights that reflect the connection’s strength bind every node in a given layer together. The designed neural network controller thereby obtained is trained using the target values to find out the desired mean square error. The
back-propagation technique adjusts the weights each time the output signal is compared to the desired output signal during training.

![Energy Management Strategy for Hybrid Electric Vehicles](image)

**Figure 8.** Energy management strategy for HEVs.

![Generated proposed ANN model](image)

**Figure 9.** Generated proposed ANN model.

### Genetic Algorithm in Speed Control of HEVs

The genetic algorithm is an adaptive heuristic, a stochastic global search technique that was first introduced by John Holland in the 1960s, and is motivated by Darwinian evolutionary concepts using the survival of the fittest as a guiding principle. It offers different approaches to tackle high-dimensional, nonlinear problems in the real world by intelligently utilizing a population of potential answers inside a specified search space. In a GA-based optimization process, individuals are chosen based on their fitness levels to produce a population, which is a random collection of approximations (binary or decimal strings). New, more appropriate individuals are produced at each generation based on natural processes including reproduction, crossover, mutation, etc. Typically, fitness represents the value of the objective function in an optimization problem. After a certain number of generations, or earlier if a particularly good answer is found, the process comes to an end as Figure 10 describes. Other than the fitness levels and the purpose, this parallel, global search technique does not necessitate any derivative information or auxiliary knowledge. In [35], smooth throttle movement and the quickest settling time, which will reduce the controlled system’s mistakes, are the goals. The fitness function establishes a connection to the application where a suitable weighted function is constructed to evaluate the performance of each chromosome in the population while taking into account each constraint. The method for minimizing the parameters is included in the objective function. This signifies that the best solution to fulfill the predetermined fitness function has been discovered.

The system’s objective is to provide a controller that guarantees the best speed-tracking performance. GA is used to calculate the optimum value of the variables based on the best dynamic performance and a domain search of the variable [35].
Fuzzy Logic Control Strategy in HEVs for Reducing Fuel Consumption

Considering that the HEV energy management system contains multiple subsystems and has the characteristics of non-linear and time-varying, fuzzy logic rules are applied to manage and control it. The fuzzy logic rule-based energy management strategy is used to deal with non-linear and uncertain issues since fuzzy control has the advantage of real-time control and strong robustness. The working mode and power of HEVs are divided based on fuzzy logic rules. Through fuzzing the vehicle speed, SOC, torque, and power, reasonable control of the HEV energy management system can be achieved, and the overall performance of the vehicle can be improved.

The fuzzy logic control strategy as highlighted in Figure 11 is selected because of its adaptability under complex working conditions. The required torque, battery SOC, and vehicle speed are selected as the input of the fuzzy logic controller. Fuzzification and defuzzification are performed, and fuzzy subsets and rules are made by looking up the information.

Unlike the driving mode fuzzy logic control, dual fuzzy logic control not only considers driving conditions but also takes how to make full use of the brake energy into consideration. As the following Figure 12 shows, dual fuzzy logic control contains two modes: driving mode and brake mode. The basic idea of the dual fuzzy logic control is to recycle the brake energy as much as possible under the condition that the dynamic performance must be met.

Deterministic Rule-Based Control Strategy in HEVs for Fuel Consumption

The deterministic rule-based control strategy is based on the concept of load balance. Its main idea is to coordinate and transfer the internal combustion engine’s working point through the electric motor so that the engine can work in the high-efficiency region as much as possible to obtain higher fuel economy. The working range of the engine is usually defined by theoretical analysis and engineering experience. For example, the working area of the engine can be divided according to the static working efficiency map of the engine. The control variables (power demand, vehicle speed, acceleration signal, battery SOC, etc.)
can be used to determine the working area of the engine and select the working mode for the HEVs so that the vehicles operate in the high-efficiency area as Figure 13 below shows.

Figure 11. Fuzzy logic control basic structure.

Figure 12. Dual fuzzy logic control strategy.

Figure 13. Overview flow chart of deterministic rules.

According to Dextreit’s study [38], the formulation of the rule is mainly through dividing the engine working area into high-load, medium-load, and low-load areas, and calculating the current power demand by combining the accelerator pedal opening and the opening change rate to determine the corresponding working mode.

The deterministic rule-based control strategy was established based on the state of core power components, and various working modes were classified. The shifting condition
between working modes and the torque distribution rules were decided. After adjusting the thresholds of the control parameters and confirming the state flow, a deterministic rule-based controller was developed.

Under CTUDC working conditions, not only does fuzzy logic control reduce the speed error compared with the deterministic rule-based control, but it also improves fuel economy performance.

Reinforcement Learning in HEVs Energy Management

Along with supervised and unsupervised learning, reinforcement learning is a sort of learning process used in machine learning. When comparing these three, however, reinforcement learning differs slightly from the other two. Here, as shown in Figure 14 we use the idea of rewarding every successful outcome as the foundation for our algorithm.

![Figure 14. Scheme of the typical agent-environment interaction for reinforcement learning.](image)

Planning and optimization tasks benefit greatly from reinforcement learning (RL), in particular, because an agent learns efficiently, model-free, and through direct contact with its environment. Deep reinforcement learning, a combination of RL and neural networks, permits the application to use very complex domains with high-dimensional sensory input, in contrast to classic reinforcement learning methods, which are restricted to very simple and low dimensional situations [39].

The development of effective operating strategies for hybrid electric vehicles uses deep reinforcement learning. The underlying research in [39] demonstrated a reinforcement learning agent’s capacity to acquire almost optimal operating strategies without any prior knowledge of the route and shows tremendous promise for the addition of more variables to the optimization process.

When it comes to processing more information about real-world driving scenarios using conventional methodologies, the energy management of hybrid electric vehicles presents significant problems for automakers. A deep reinforcement learning framework has been developed in [40–42] that has a lot of promise for resolving many of those issues. The ability of a deep RL agent to achieve almost ideal fuel consumption outcomes with a locally trained strategy that can be used online in the vehicle has been demonstrated in [39]. Furthermore, deep reinforcement learning makes it possible to effectively include additional optimization criteria.

Conclusion: Deterministic rule-based energy management strategies are often based on the experience of engineers, the division of work modes, and static energy efficiency maps to formulate. The idea is simple to understand; the amount of calculation is small; and the method is easy to implement. However, there is a bad side to this strategy. Deterministic rule-based energy management strategies cannot adapt to varying working conditions and the demand of dynamic changes in reality. Its adaptability is not strong enough to achieve optimal control. To seek the optimization of performance and the real-time adaptability of working conditions, fuzzy control is integrated into the rule-based control strategy on this basis.

The fuzzy logic rule-based energy management strategy is not dependent on the accuracy of the system model, and has strong robustness and deductibility, making it more suitable for the control of complex nonlinear hybrid power systems. However, it still needs to rely on engineering experience to achieve an accurate control effect, and
it cannot guarantee optimal control. Often through other intelligent control algorithms such as reinforcement learning, better results are obtained as well as improved control performance in HEVs, as shown above.

2.2.2. AI Algorithms in Transient Control

A transient event is a short-lived burst of energy in a system caused by a sudden change of state. The source of the transient energy may be an internal event or a nearby event. The energy then couples to other parts of the system, typically appearing as a short burst of oscillation. Internal combustion engine research has typically concentrated on steady-state performance. While the most critical conditions faced by industrial or marine engines are met during transients, the daily driving schedule of automobile and truck engines is fundamentally linked to unsteady operation. The research of transient engine operation is an essential scientific goal because the transient action of turbocharged diesel engines has unfavorably been linked to poor drivability and overshoot in particulate and gaseous emissions. In engine transient operation, all the intricate thermodynamic and dynamic phenomena that a diesel engine encounters during load rise, acceleration, cold starting, or transient cycle are thoroughly covered. The examination discusses a variety of subjects, including heat transfer, combustion, air supply, and friction, after starting with the primary and most significant turbocharger lag issue.

Dynamic Feedforward Algorithm in Transient Control

The studies [43] suggest a method for creating an automated transient feedforward (FF) control system. To resolve a dynamic optimization problem for quick transients, it uses optimal control theory as demonstrated in Figure 15. Thus, the engine is replaced by a partially physics-based model. The pertinent data is taken from the best solutions and saved in maps spanned by engine speed and torque gradient.

![Figure 15. FF control based on the steady-state actuator set-point map.](image)

Applying the proposed methods will result in a significant increase in fuel efficiency without lowering emission levels. Additionally, when the Nox emission limits are changed, the optimization framework exhibits good sensitivity to the Nox–fuel tradeoff. As a result, depending on how the emission level targets are tuned, the optimization tool can offer varying degrees of fuel reduction.

Reinforcement Learning Algorithm in Transient Operations

A well-liked model for sequential decision-making under uncertainty is reinforcement learning (RL). A typical RL algorithm operates with little information about the environment and little feedback on how well the judgments were made. Learning agents need to be able to selectively disregard unimportant details to function well in complicated contexts.

Deep reinforcement learning (DRL) enables a general learning process without taking into account a specific understanding of the job. However, since the initial policy behavior is nearly random and a high number of interactions with the environment are necessary, such an algorithm cannot be taught directly in a real-world environment while adhering to the specified safety criteria. Articles [44] suggest a control architecture built on DRL that pushes training toward taking place right in the dynamic real-world environment.
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Figure 17 describes two actions (a) and (b) where the agent is learning to walk from the original state SA to the target state ST. The reward for reaching the target state is +100 and all other nontarget rewards are 0. This approach will bias the action exploration toward the higher augmented rewards, therefore realizing the demonstration knowledge transfer from a different angle.

Figure 17. Reward shaping mechanism.

Ref. [44] proposed a powertrain control framework based on the DQN that might directly train its policy behavior in a transitory real-world environment without compromising safety. Using the boost control problem for a diesel engine with a VGT as an example, the proposed algorithm enhanced the initial performance by 74.6% and the learning efficiency by an order of magnitude while satisfying the safety constraint. It is recommended that future DRL-based powertrain control be built given that the form of the previous knowledge in this research was simple to obtain for many industrial powertrain problems, and the proposed algorithm can implement the “model-free” notion in the strict sense [44,45].
Conclusion: The control ecosystem may present a complex web of interrelated technologies, but it may also be made simpler by thinking of it as an ever-evolving branch of a family tree. Each control system technology provides unique features not available in prior technologies. The use of AI technologies to enhance control is the most recent development in control strategy evolution. The use of reinforcement learning-based controls is one of the most recent developments in this field and provides the best results in terms of efficiency, implementation, cost, and time management.

2.3. Artificial Intelligence (AI) Algorithms in Engine Diagnosis

Engine diagnosis refers to any type of manual or computerized evaluation used to identify potential issues leading to malfunction. The first artificial neural network (ANN) was released in the early 1940s. It took several decades, nevertheless, for ANNs to be practically useful for solving engineering issues, from high-precision, input–output, black-box models to reliable classifiers and pattern recognition systems. For ICE applications, ANN has been used extensively. One of these applications is the prediction of engine performance metrics and emissions, such as Nox, HC, and CO. Another one is engine diagnostics (e.g., misfire detection, knock, etc).

2.3.1. AI Algorithms in Misfire Detection

Misfire in an internal combustion engine refers to a loss of power during the operating process caused by non-burning or inadequate cylinder pressure. Because of its significant impact on emissions, engine block vibration, and shaft torsional vibration, misfire detection is a requirement in most nations’ emissions rules [46]. Misfire is a typical failure situation in diesel engines, and it is gaining attention because it can significantly reduce the engine’s power and economic performance [47]. Insufficient fuel injection, poor fuel quality, insufficient ignition energy, or mechanical failure, among other things, can cause engine misfires. Because a misfire problem can result in irregular engine operation and pollution, several researchers have been working to develop accurate and real-time misfire detection algorithms [48]. Electronic control units are used in conjunction with numerous sensors on modern diesel engines to gather a wealth of engine operating data. Misfire occurrences are still difficult to pinpoint using straightforward reasoning or an algorithm. Misfire may be caused by either mechanical or electrical component failure. Examples include solenoid drive failure, injection nozzle blockage, decreased compression ratio (as a result of worn piston rings), and insufficient air–fuel mixture inside the cylinder.

Scholars all over the world have conducted extensive research on the diesel engine misfire fault and put forward a variety of diagnostic methods, such as the ion current [49], the radiated noise [50]. Recently, Konstantin Dragomiretskiy [51] proposed a new variable adaptive decomposition method, otherwise known as variational mode decomposition (VMD). Engine misfire detection techniques can be classified based on the sensor signals used, such as the method using engine body vibration signal [52], the method using acoustic signal [53], and the method monitoring in-cylinder iron current [49]. Because the vibration signal is sampled with high resolution and is related to in-cylinder combustion, the approach using engine body vibration signal could sample a lot of data. Processing vibration data, on the other hand, necessitates a significant amount of computation. In practical implementation, the acoustic signal approach has not overcome the problem of noise interference. The sensor’s response time limits the method for assessing the temperature of exhaust gas.

Many researchers have embraced the crank speed method because the crank speed can be sampled very readily and is not easily polluted by an uncorrelated noise. Physical misfire detection methods based on crank speed can be divided into two categories: data-driven diagnosis algorithms and model-based algorithms. The model-based method is used to diagnose engine misfires by using the engine dynamic model to construct a link between crank speed and in-cylinder pressure.
Based on the experimental crank speed of a four-cylinder engine, Zheng et al. [54] devised a Luenberger sliding mode observer to estimate engine combustion torque. If properly implemented, the model-based approach can produce very accurate results. However, the method requires exact engine model parameters, which are difficult to estimate accurately. The damping, for example, is impossible to quantify. In the meantime, the complexity of a model-based approach may prevent its implementation in real time. As a result, this approach is not extensively used in industrial settings. Instead of determining the excitation torque or in-cylinder pressure, data-driven diagnosis algorithms give another method of misfire detection, in which misfire-related variables are retrieved directly from crank speed. Misfire is recognized by separating fault-related characteristics from fault-free characteristics.

Machine learning methods have advanced quickly in the last two decades and have been used in misfire detection studies [55]. In comparison to techniques that calculate one or a few human-designed signs for misfire detection, the machine learning algorithm could extract more defect information from a single signal or analyze multiple signals at once. According to the literature, the machine learning algorithm employed not only the crank speed but also the engine vibration and in-cylinder pressure.

Artificial Neural Networks (NN/ANN) Algorithms in Misfire Detection

A V6-cylinder Deutz TCD2015 turbocharged diesel engine was used on a dynamometer test bench. The experiment aimed to obtain some engine running parameters at normal conditions and misfire. These parameters included engine speed, power, fuel efficiency, intake, exhaust, cooling temperature, etc. The parameters were used to compose many groups of data vectors, which could be used as the data inputs to train the neural network. All relevant parameters were recorded when the engine ran under steady-state conditions [56].

A three-layer network was used in the [56] study. The input layer received information from the outside and fed forward through a hidden layer to the outputs, repeating the whole process until ideal results were achieved. The data collecting system can gather large data about the test diesel engine. The attention was on choosing the relevant parameters to create training vectors. Despite the trained neural network’s learned target error being satisfied to the limits, some misdetection of misfire identified by numbers 1, 2, 3 and 4 still occurred, as shown in the Figure 18 below. An effort was made to change the input vectors’ makeups, which are seen to be crucial components of a useful network. It was further noted that misfire increases the in-cycle speed variation. It is crucial to include this information in the training samples to produce consistent and accurate detection results as Figure 19 highlights. Because the in-cycle speed variation differs between the normal mode and the misfire mode. The new training vectors’ additional parameters were chosen to be the maximum speed variation.

Conclusion: Since there are so many variables that might affect diesel misfire events, it might be challenging to draw up a straightforward physical model that can accurately represent such a situation as described above. An artificial neural network model that is described above provides the best results because it is more applicable in countless circumstances than traditional modeling approaches. When sufficient test data are available, this technique can be used to predict the intended output parameters, and it has been extensively employed in a variety of business domains.

2.3.2. AI Algorithms in Knock Detection

Engine knock is a tapping, pinging sound that gets louder and more obnoxious as you accelerate. Engine knock, also known as detonation, happens when the temperature or pressure of the end gases—the unburned air and fuel mixture—exceed a certain point, automatically igniting the end gases. A shock wave is created as a result, which causes the pressure inside the cylinder to rise quickly. If significant banging is not repaired, damage to the pistons, rings, and exhaust valves may follow. Additionally, the majority of car buyers
dislike the sound of an aggressive engine knock. The likelihood of knocking is influenced by a variety of elements, including mechanical, electrical, environmental, misuse and many more as shown in Figure 20.

![Figure 18. Verification of trained NN at the first trial.](image1)

![Figure 19. The 100% accuracy final misfire detection after including transient speed information.](image2)

Engine knock restricts the ability to optimize spark timing for a specific air–fuel ratio to improve power and fuel efficiency. The best power and fuel efficiency are obtained when knock detection and ignition timing are controlled to allow an engine to operate at the knock threshold. When a spark plug is used to ignite a mixture of fuel and air, normal combustion is when the combustion proceeds smoothly from the point of ignition to the cylinder walls.
To prevent such abnormal combustion and the associated risks, the ignition is delayed and the compression ratio is limited. Those measures harm efficiency and effectively place engine knock as a restriction on engine operation [57]. To avoid, reduce, or even completely prevent auto-ignition incidents, manufacturers have created some techniques. Using high-octane, “knock-resistant” fuels or more conservative spark timing calibration maps are two examples. Exhaust gas recirculation (EGR) systems, which employ a portion of the exhausts from the previous combustion to cool the present combustion, have received a lot of attention. The resultant temperature drop successfully reduces emissions, boosts efficiency, and successfully creates fewer knock-prone circumstances [58]. Recent methods have also demonstrated that directly infusing water into the cylinder gradually reduces knock intensity, overall combustion stability, and emission of many exhaust gases [59]. Although the approach has a good effect, it is also linked to higher soot emissions [60]. Conventional knock detection works by comparing incoming vibration or pressure data with manually predetermined thresholds, assuming auto-ignition whenever that value is exceeded. When these threshold values are exceeded, the ignition time is typically delayed to stabilize the combustion process [61].

![Figure 20. Factors that contribute to knock.](image)

The majority of the underlying methodology of detecting mechanisms share one significant shortcoming, despite the existence of classification methods based on more intricate physics and chemistry-inspired approaches: They need to be meticulously calibrated to an engine’s current operating circumstances. However, this results in the majority of detection techniques being highly tailored for the engine they have been created for, and, in some instances, being even more fitted to one specific operating point [61].

Recently, artificial intelligence solutions have started to gain traction. Traditional physics-based knock modeling often uses chemical kinetics models or empirical correlations to approximate processes occurring during the combustion process.

On the other hand, Netzer et al. [62] present a series of chemical and physical models that, in addition to identifying autoignition, also quantify its severity. Primarily based on fuel properties, the model is calibrated for deployment at the knock limit. A weighted ring extreme learning machine for forecasting heat release-related values is presented in [63] as a solution to the larger issue of engine control for HCCI engines. The model is usable in real applications after being pre-trained on offline data and adapted to the current engine
conditions via online re-training. The algorithm analyzes a six-dimensional vector as input, recording various pressure levels throughout a cycle, the beginning of ignition, the injection pulse width, and the most recent data on heat release.

Convolutional Neural Network (CNN) Algorithms in Knock Detection

A convolutional neural network (CNN) is a network architecture for deep learning that learns directly from data. CNNs are particularly useful for finding patterns to recognize objects, classes, and categories. They can also be quite effective for classifying audio, time series, and signal data.

It is intended that training and dataset labeling only need to be performed once, and that the model can generalize to different engines with little to no changes [61]. It was determined that using in-cylinder pressure sensors was superior to using engine block vibration sensors because the latter had a significant reliance on sensor location and generated a lot of noise. Additionally, earlier studies have found that in-cylinder pressure traces produce the most accurate detection results [64].

Figure 21 below introduced a 1D convolutional neural network approach for knock detection in a spark ignition combustion engine. The model demonstrated a high degree of classification accuracy despite having been trained on data from multiple operating points of three different engines. For a multiclass task, the model categorized 78% of cycles perfectly and over 90% at, at most, one position from the ground truth. A binary distinction between “knocking” and “non-knocking” cycles produced consistent results of over 92% accuracy. Thus, in all trials carried out for this investigation, the suggested CNN models significantly exceed the widely-used MAPO test bench knock criterion as well as two PCA-based criteria [61].

Figure 21. Fundamental structure of a CNN model.

Reinforcement Learning Algorithm in Knock Detection

An effective approach to finding engine knock is to gather vibration signals from the engine cylinder block. Studies [65] suggested an engine vibration signal-based intelligent engine knock detection system. First, variational mode decomposition (VMD), which divides the initial time domain signals into many intrinsic mode functions (IMFs), is used to create filtered signals. Furthermore, a genetic algorithm (GA) is used to optimize the balancing parameter values and the number of IMF modes. Then, IMFs that are sensitive subcomponents for signal reconstruction and have sample entropy values above the mean are chosen. To extract features from the denoised signals, a multiple-feature learning method is used that simultaneously takes into account temporal domain statistical analysis (TDSA), multi-fractal detrended fluctuation analysis (MFDFA), and alpha-stable distribution (ASD). To avoid the sensitivity of the hyperparameters in the traditional machine learning algorithm, the extracted features are trained by the sparse Bayesian extreme learning machine (SBELM).

The raw engine data is gathered using a test rig. The suggested integrated engine knock detection method shown in Figure 22 achieves a classification accuracy of 98.27% and has the best signal processing to feature classification strategy when compared to other technology combinations [65].
2.3.3. AI Algorithms in Intake System Leakage Detection

An intake system is a set of components that essentially allows an internal combustion engine to inhale, in the same way that the exhaust system allows it to exhale. Early automotive intake systems were simply inlets that allowed air to pass unimpeded into the carburetor, but modern systems are much more complex.

Leaks in a gasoline engine’s air intake system (AIS) can impair the operation and result in poor fuel economy, air pollution, and sluggish driving performance. To increase dependability and reduce fuel consumption, the diagnosis and prognosis of air leakage have become essential. OBDII (On-Board Diagnostics), an environmental-based legislative mandate, has made the on-board diagnosis of automobile engines more significant. Repairability, availability, and vehicle protection are other justifications for including diagnostics in automobiles. Today, diagnostics take up to 50% of engine management systems. If the engine has an air-mass flow sensor, a leak will make the sensor’s reading of the amount of air entering the combustion chamber inaccurate. The air–fuel ratio will then deviate as a result of this. When lambda no longer equals 1, an air–fuel ratio variation becomes severe because it increases emissions. Additionally, drivability will deteriorate, and leaks will cause horsepower to be lost, especially in turbocharged engines. Consequently, this effort aims to compare and provide a technique that can precisely identify leaks. It is important to detect leakages with an area as small as some square millimeters. Obtaining an idea of the extent of the leakage is crucial for engine management, and this is performed to determine the proper course of action, such as issuing the motorist a warning. Furthermore, if the leak’s size is known, the control algorithm can be changed to ensure that the leak’s impact on emissions is minimal, at the very least.

Neural Network Algorithms in Intake System Leakage Detection

For diesel air paths, a method for leak detection and characterization was developed, as shown in Figure 23 below. Two blocks make up the suggested strategy: a training block...
and a decision block. The initial one is carried out offline and incorporates a neural network based on the Levenberg–Marquardt algorithm with a feature selection algorithm. The L-M function was selected due to its precision and versatility; it combines two distinct strategies based on where the current solution stands concerning the best one. The second block makes use of the neural model developed during the training phase to identify and classify leaks that develop in the air path system. Using the MSE index, the detection and characterization capability is assessed. The suggested method successfully addresses the issue of leak characterization and detection, particularly when dealing with minor leakage at crucial operational locations (low speed and torque) [66].

![Detection and characterization scheme.](image)

**Figure 23.** Detection and characterization scheme.

Conclusion: It is crucial to keep in mind that models created using empirical data or physical phenomena are frequently constructed in idealized settings and may not accurately reflect the actual dynamics or nonlinear behavior of engines. For that reason, using artificial intelligence for leak detection is the best choice because it provides great use of the numerous real-time engine characteristics in terms of data that we can obtain nowadays. A promising leak detection method using neural networks is summarized above.

3. Conclusions

Engine performance is expressed in terms of emission control and fuel economy. Artificial neural networks (NNs) are the most often utilized models for these applications because they are global approximators that can represent the nonlinear properties of a complex system by utilizing a nonlinear activation function. They provide very good efficiency results in both emission control and fuel economy because of easily attainable benchmarks. Engine control and engine diagnosis, on the other hand, due to the complex nature of processes involved and the presence of big data, provide challenges that are not solved by conventional techniques of fuzzy logic rule or by neural networks. In the HEV
application domain, for instance, the fuzzy logic rule still needs to rely on engineering experience to achieve an accurate control effect, and it cannot guarantee optimal control. That makes reinforcement learning more adaptable in engine control, hence leading to better results as well as improved control performance. Another notable example is in the knock detection part of engine diagnosis; a convolutional neural network (CNN) as a classification method that is trained to judge from self-learned features instead of manual input parameters equivalent to calibrated thresholds to reduce this dependence on specific engine conditions was introduced, and a binary distinction between “knocking” and “non-knocking” cycles produced consistent results of over 92% accuracy. However, using a novel sparse Bayesian extreme learning machine algorithm, the engine knock detection method achieves a classification accuracy of 98.27% and has the best signal processing to feature classification strategy when compared to other technology combinations.

4. Summary and Outlook

The state-of-the-art introduction of artificial intelligence into engine operations has been analyzed in this review. Three main sections of the review, namely, engine performance, engine control, and engine diagnosis, are analyzed. After deep research on the web, scientific journals, technical reports, and conference proceedings, the following conclusions were reached.

The review shows that the mainstream to follow is artificial intelligence because of the many advantages, such as big data, high adaptability, improved accuracy, and many more. In addition to that, artificial intelligence is a discipline that is always evolving in terms of innovation and new technologies. Reinforcement learning, for example, is a new aspect that is being studied by many researchers. Many governments are introducing new regulations, and to cope with the ever-changing nature of the world, AI provides all the necessary adjustments, as well as solutions in terms of easy implementation.

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