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# Application of Artificial Neural Networks in Predicting Internal Combustion Engine Performance and Emission Characteristics: A Review of Key Methodologies and Findings

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ABSTRACT

The global need for fuel-efficient coupled with minimizing the environmental impacts of ICEs. This review paper highlights how different ANN methodologies such as backpropagation, recurrent neural networks (RNNs), and long short-term memory (LSTM) networks have been applied to optimize engine calibration, improve fuel efficiency, and minimize emissions across a wide range of fuel blends, including hydrogen-gasoline and ethanol-gasoline mixtures. The research focuses on the application of ANN models to predict performance indicators such as brake thermal efficiency, brake-specific fuel consumption, and emissions, reducing reliance on costly and time-consuming experimental tests. The methodology involved a systematic review of peer-reviewed studies published between 2010 and 2024. Studies were selected based on criteria such as relevance to ICE performance and emission control, use of ANN methodologies, and the availability of experimental or simulation data for validation. involves the use of advanced ANN architectures, including backpropagation, RNNs, and LSTM networks, to establish nonlinear relationships between input parameters such as engine speed, load, and fuel type, and output performance indicators. Findings show that comparison between real model and developed program enhanced from ANN model make a difference prediction capability for engine performance enhanced by at least 10 to 15 % of the traditional modeling. techniques, provide better calibration method of ICEs for better fuel consumption. efficiency and reduced emissions. This present study seeks to establish itself in matters that have not been explored in other papers or researches as follows. integration of Hybrid ANN models, which are better than conventional methods in two major trends, one of which is the improvement of the predictive accuracy and the other is the achievement of increased computational efficiency. It is found that the ANN methodologies presents a strong armory in improving the performance of ICE coupled with lowering of emissions with the possibilities of additions for further enhancements of the technology through the incorporation of other machines use of learning techniques in the future studies.

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## 1. Introduction

Increased concern with the fuel consumption and emissions of ICEs has led to innovation in the structure of ICEs and fuel composition Modern changes in the ICEs and fuels are to address environmental standards without compromise in engine efficiency. In the current worldwide development of more efficient ICE technologies, new approaches that facilitate better control of fuel injection and burning, namely GDI and HCCI, are viewed as pivotal. Also, the incorporation of exhaust gas recirculation (EGR) systems and variable valve timing (VVT) has enhanced the combustion process accuracy through in-cylinder gas management and also has increased volumetric efficiency. [1]-[4]. At the same time, there has been development in the fuel parameters and in the option of using new fuel like hydrogen, ethanol and CNG. For instance, the incorporation of hydrogen into gasoline in hybrid hydrogen-gasoline engines (HHGE) enhances the brake thermal efficiency (BTE) and decreases the nitrogen oxide (NOx) emissions because of a proper air-fuel mixture for lean combustion. [5]-[9]. Additionally, diesel, gasoline, LPG, CNG, and LNG are a concern because of increased industrial rate and growth of modern societies which require these fuels. In addition, the supply of these fuels will decrease within the next 50 years. Moreover, the practical implications of using ANNs for ICE optimization extend beyond theoretical advancements. By enabling more efficient engine design, improving real-time calibration, aiding regulatory compliance, and enhancing market competitiveness, ANN models provide significant value for engine manufacturers, calibration engineers, policymakers, and other stakeholders in the automotive industry. As ANNs continue to evolve, their impact on cost reduction, environmental sustainability, and innovation will likely drive further adoption across the industry [10]-[12].

Specific fuel properties, such as octane rating and viscosity, also play critical roles in engine performance. For example, higher oxidation fuels allow engines to work at higher compression ratios offering increased power and thermal efficiency while, leaner or less viscous fuels enhance fuel mixture formation during injection thus promoting combustion stability [13]-[17]. Additionally, improvements in the injection timing including the late injection in GDI engines have been known to decrease PM emissions and improve the combustion efficiency under various load conditions [18]-[20]. Hence, a number of approaches has been addressed by researchers to enhance the performance of internal combustion engines (ICEs) and to adopt other green fuels and more extensive studies on ICE characteristic, engine design, reduction of emissions and emission control technologies for ICEs as a result of burning conventional fossil fuels and other fuels. Mathematical modeling can be helpful in the prediction of the engine performance and emission characteristic, however more development is required on the existing model and identification of the proper alternative fuel. Nevertheless, this has led to the improvement of the engine experimental tests exponentially which has made the usage of modelling and numerical approaches which uses statistical methods and DOE methodology to cut down on the engine tests [21]-[23].

Further, understanding the nature and other relations as well as defining correlations between many input variables might be difficult, which exert negative influence on the improvement of the needed approximate solution. This problem may be compounded by the fact that the parameters used in the data acquisition system of a dynamometer test rig tend to produce noise. On the other hand trained artificial neural networks provide the nonlinear matching between input variables and desired outputs at no extra cost [24]-[27]. The issue of nonlinear input-output matching has pertinently raised eyebrows and this has been solved by the coming into play of artificial neural networks commonly referred to as ANNs. Unlike prior approaches that may provide exact results that are very sensitive to parameters of input information, ANNs can produce reliable outcomes which are not affected by marginal fluctuations of measurements, thereby making them promising solutions for many problems.

ANNs are being employed increasingly in system diagnosis because they operate in a way that is like the biological neural system. ANNs can be used as prediction models for definite applications, provided that they have been adequately trained. It has to be noted that these can be adjusted with the newer scheme of data and are intended to undergo certain learning processes. [28]-[30]. An ANN model which considers many anticipant variables can predict many consequent variables [31], [32]. ANNs may represent a system without previous knowledge of the process linkages, in contrast to traditional modeling techniques [33]. In addition to being cost-effective, this method is efficient in analyzing both the individual and combined components of the experimental variables that lead to the output responses [34]. Furthermore, ANN-based models outperform other optimization techniques as particle swarm optimization (PSO) and genetic algorithms (GAs). Consequently, the ANN model technique has drawn interest from several technical domains, such as catalysis [35], analytical chemistry [36], [37], solar-based energy systems [38], [39], cooling systems [40], [41], the food sector, system architecture, and production process optimization [42]-[47].

(PSO) is a population-based optimization technique that mimics the social behavior of birds or fish. It is well-suited for optimizing continuous, nonlinear functions and has been used for ICE parameter optimization tasks, such as tuning engine control unit (ECU) settings and optimizing fuel injection timing. However, PSO can suffer from premature convergence, where the solution settles into a local minimum, particularly in complex, high-dimensional problems involving multiple conflicting objectives (e.g., balancing fuel efficiency and emissions simultaneously). Moreover, PSO lacks the ability to learn and generalize from historical data, requiring each optimization problem to be solved independently [48]-[50]. Genetic Algorithms (GAs), another population-based optimization technique, are inspired by natural selection and have been applied to ICE optimization for tasks such as optimizing valve timing, compression ratios, and fuel injection. GAs are particularly effective in exploring large solution spaces and handling discrete variables, making them useful for design optimization in engineering. However, GAs tend to be computationally intensive, often requiring multiple iterations to evolve an optimal solution. Additionally, like PSO, GAs are not inherently designed to model relationships from data but are instead used to search for optimal solutions within predefined constraints [11], [51], [52] .

In contrast, Artificial Neural Networks (ANNs) offer several key advantages that make them particularly well-suited for ICE optimization in scenarios involving complex, nonlinear, and multidimensional datasets. Unlike PSO and GAs, ANNs are data-driven models capable of learning from data and subsequently using the data to predict engine performance over various settings and fuel blends without having to go through the optimization again. For example, while comparing ANN and GA models to predict the ICE fuel injection parameters, it was found that the prediction accuracy of ANNs was 15% higher and the time taken for computation was 20% less than that of GA as ANNs can learn from the previous data of the engine unlike GA which has to start with parameters and Train the data set Further ANNs are useful in real-time applications where goal is to achieve maximum performance in varying condition. While PSO and GAs require iterative computations that can be time-consuming in real-time scenarios, ANNs, once trained, can provide instant predictions, making them highly efficient for adaptive engine control systems. In comparing ANN-based models to other search algorithms including PSO and GAs for real-time calibration of engines, the results have confirmed the effectiveness of this approach in terms of speed of prediction and the ability to extrapolate to new conditions of engine load and fuel type [11], [53].

Several studies have found ANN models helpful when studying ICEs to address complex and/or nonlinear problems concerning the efficiency and emission of engines that are operated by AFs and mapping of input parameters as well as output responses [54]-[57]. In addition, artificial neural networks constitute one of three primary modelling strategies, namely, white-, gray-, and black-box modelling techniques. The major difference between these approaches is that in the first one, the physical understanding of the representations and interpretability of the model is higher. In white-box modelling, it means that the end product, or system, is fully understood and the model is derived from known physical equations specifying the behavior of the system. Still, concerning the ICEs, the idea of white-box models presupposes a detailed understanding of such processes as thermodynamics, fluid mechanics, and chemical kinetics to predict engine performance. For instance, a white-box model of an ICE might employ first principles equations to estimate cylinder pressure, heat transfer, and fuel-air mixture given measurable geometry characteristics of the cylinder, valve timing, and properties of fuel among others. These models are characterized by high accuracy, but they need detailed information about the engine and the car's domain in general, which is a drawback if such data are not available. This is because, the correlations between variables and parameters are made under the deployment of physical laws and hence, highly transparent and interpretable. On the other hand, black-box modelling describes a situation that does not require much information about the mechanism of the system and it depends on the input-output data in the construction of the model. Further, in this case, the model works in a way where the input-output relationship doesn't have a specific significance except for the actual mathematical model of the black box that predicts results based on the relationship seen in the data. Artificial neural networks (ANNs) are instance of black-box models which have been employed in ICE optimization. In black-box modeling, the internal combustion processes of the engine are not explicitly modeled; instead, the ANN learns patterns from historical data on engine inputs (e.g., fuel type, injection timing, and engine load) and outputs (e.g., brake thermal efficiency, NOx emissions) to predict future engine performance. While black-box models can handle highly complex and nonlinear relationships, they often lack transparency, making it difficult to interpret the internal mechanics of the model's predictions. involves matching inputs and outputs while mapping, and does not require any understanding of the relations between them and therefore is non-transparent and non-interpretable. Hybrid models is another type of models it has some features of both white-box and black-box models and it is called gray-box models. It is a hybrid approach where some components of a given system are captured by first principles, where the nature of systems behavior is known whereas the others components are modeled using statistical tools where the behavior is unknown. For instance, in an ICE, the thermodynamic cycle may be simulated by physical equations while the combustion process could be simulated using test results on the engines. This approach can provide better accuracy and flexibility of the model when the physics-based understanding is not sufficient from the first principles as in case of turbulent combustion or complex fuel characteristics [57]-[59].

Although, ANNs have fairly good prospects in enhancing internal combustion engines (ICE) performance and reducing emissions, there are some critical issues and prospects that need to be further addressed in further research. Based on the limitations and challenges identified in current studies, the following key areas offer promising avenues for future research: Despite the developments in ICE performance and emissions provided by ANNs, future studies should consider enhancing interpretability of the model, decreasing the computational costs, dealing with limited data, implementing AF technology, and hybridisation. That is why the selected areas: (a) improvement in convergence based on the ANN structure, and (b) a novel approach to the selection of input variables for ICE optimization, can help researchers to fill present gaps and advance the state-of-art.

1. Improving Model Interpretability
   - Another major drawback for most ANNs is their less interpretability since they are categorized as a black box model. Whereas, further studies should be devoted to the development of the approaches that allow incorporating XAI methods into ANN models. If one could learn to 'visualize' how ANNs make a decision or predict engine performance then decision–makers such as engineers could rely on the prediction yet comprehend how ANNs came to this conclusion. This is especially so in safety-critical applications wherein the outputs of analysis models can be relied on absolutely.
   - Actionable Recommendation: Further studies should be conducted on the integration of physics-aware ANNs and physics-based models that involve the design of the ANN architecture that has incorporation of available data of the engine motion. This may offered an interface between the revelation of the conventional models and the self predicting capability of ANN's.

2. Optimizing ANN Models for Real-Time Applications

- As ANNs become more prevalent in ICE optimization, there is a growing need for models that can be deployed in real-time engine control systems. However, the high computational demands of deep learning architectures often limit their feasibility in such applications. Future research should focus on developing lightweight, efficient ANN models that can be implemented in real-time without sacrificing accuracy.
- Actionable Recommendation: Research should focus on exploring model compression techniques (e.g., pruning, quantization) and edge computing to deploy ANNs directly in engine control units (ECUs) or other resource-constrained environments. Additionally, leveraging advancements in reinforcement learning could allow for more adaptive, real-time engine calibration systems that improve with use.

3. Addressing Data Scarcity and Overfitting

- A major limitation of ANNs is their dependence on large, high-quality datasets. In many ICE optimization tasks, obtaining sufficient training data is challenging, particularly for novel engine designs or alternative fuel types. Research into methods for improving the robustness of ANN models in data-scarce environments is crucial. Moreover, overfitting remains a persistent issue when models are trained on small datasets or datasets that do not cover the full range of operating conditions.
- Actionable Recommendation: Further work should explore the application of transfer learning so as to enable the training of ANNs on one kind of an engine or fuel and adapt them to other conditions with minimal data. Further, methods, including data augmentation, a process of adding variations of the existing data and the regularization of the model parameters, could be employed to minimize overfitting and enhance generalization in situations where there is scarce data.

4. Incorporating Emerging Fuel Technologies

- As the world emphasizes the use of more advanced, safer, and environmentally friendly fuels including hydrogen, biofuels, and synthetic fuels, further research I expected to advance ANN models to suit these new fuels. Despite the prospects of ANNs applied to the problem of optimization of conventional fuel blends, more work is needed to comprehend how these models can help to capture the behavior of the engine about lesser conventional fuels, the combustion of which may be more intricate.
- Actionable Recommendation: Studies should be aimed at creating ANNs that would enable one to forecast the performance and emissions of multi-fuel engines in which used fuels are applied in any sequence. Further, combining reaction kinetics and fuel property modeling with ANNs can serve to deliver an enhanced understanding of how the new generation of fuels interfaces with engines.

5. Hybrid Modeling Approaches

- While ANNs excel at capturing nonlinear relationships in engine systems, combining ANNs with physics-based models could offer the best of both worlds: on factors such as predictive accuracy and interpretability of the physical model. This would enable specific relations which are in the competence of thermodynamic or fluid dynamic model to be incorporated in the model while using ANNs to model the data relations which are more complex and difficult to model.
- Actionable Recommendation: Future research should focus on developing hybrid models that integrate the first principles of engine operation with ANN-based approaches. These models could leverage the strengths of physics-based and data-driven techniques to improve accuracy, interpretability, and generalization across a wide range of operating conditions.

6. Evaluating Long-Term Sustainability and Environmental Impact
   - With the automotive industry focusing on sustainability, future research should assess the long-term environmental impacts of ANN-optimized engines. While ANNs can be used to minimize emissions in the short term, their role in optimizing engines for lifecycle analysis (considering factors such as fuel production, engine degradation, and recyclability) should be explored further.
   - Actionable Recommendation: Researchers should integrate life cycle assessment (LCA) methodologies into ANN-based engine models to evaluate not only the emissions during operation but also the full environmental footprint of various fuels and engine designs. It could also offer a broader perspective on one of the most promising engine technologies, ANNs, and their ability to drive the industry's sustainability.

The past few years have seen Artificial Neural Networks (ANNs) being adopted as an effective means of improving efficiency as well as the emissions of internal combustion engines (ICEs). Although the usage of ANNs is on the rise, a more specific analysis of the benefits and drawbacks of ANNs concerning other modeling techniques like GA and PSO is not that rich. However, there has been relatively limited qualitative discourse on how ANN can be applied practically in actual ICE systems in aspects such as data demands, model explainability, and execution time.

This review paper aims to address these gaps by providing a thorough evaluation of the use of ANNs in ICE optimization, with a specific focus on This review paper aims to address these gaps by providing a thorough evaluation of the use of ANNs in ICE optimization, with a specific focus on:

1. Research Questions
   - Comparing ANNs with the conventional optimization methods, like GAs and PSO, with respect to prediction accuracy, computational front, and ICE modeling.
   - Over which mismatches and limitations does the practical application of ANNs pose challenges in ICE systems: Overfitting, quality of data, and computation requirements?
   - How can ANN models be further improved to enhance their usability and performance in optimizing ICEs?
2. Objectives
   - To give a state-of-art review about the use of ANN in the current ICE optimization for better performance and low emission.
   - To present the results of the comparison study between ANNs and other optimization techniques like GAs, PSO applied on ICE modeling, emphasizing on advantages and limitations.
   - To determine the main methodological drawbacks of ANNs and the problems associated with the quality of data, overfitting, and computation complexity, and give recommendations for their mitigation.
   - To identify the relevant developments for future improvements of the ANN models, for example, the use of the XAI methods for increasing transparency of the chosen algorithms, as well as the development of the hybrid modeling approaches based on the data-driven and physics-based methods.
3. Unique Contributions
   - Comparison with Alternative Techniques: Thus, this paper offers one of the first systematic analyses of ANNs against other population-based metaheuristics including GAs and PSO in an ICE performance modeling context. It features situations in which

ANNs are superior to other schemes and those in which they might be inferior, thus providing the reader with a more nuanced perspective on the usability of the technique.

- Methodological Challenges: This paper aims to highlight some of the real-life issues regarding the use of ANN in ICE optimal design involving issues to do with the availability of data, computational size, and model readability. In this regard, the review offers a link to the aspects that need to be considered when implementing ANNs in an industrial environment which helps avoid above mentioned challenges.
- Future Research Directions: The paper outlines new methods to increase the ANN models' performance and interpretability, that is to apply the XAI techniques. Further, it covers the use of a combined approach involving the use of both data-driven and physics-based models for the future enhancement of ICE modeling.

Considering this, the specific research questions, objectives, and unique contributions presented in this paper provide a systematic and well-coordinated roadmap for researchers and practitioners who may wish to conceive and develop subsequent systematic strategies to advance and apply ANN for enhancing ICE performance and emission control. The findings presented can be relevant for the theoretical advancement of ANN modeling as well as for applying engine design and optimization.

## 2. Artificial Neural Network

Various artificial neural networks (ANNs) models have been customized to predict various parameters related to internal combustion engines (ICE). The concept behind these models is that it is intended to eliminate the cost, time, and complexity associated with the use of conventional experimental methods for evaluation of the engine performance [60], [61]. Improving ANN models is very important to avoid getting caught in local optimized solutions and other ways such as the modified grid search and the random search are recommended for optimizing the model's parameters [62], [63] However, the most recent development is there in the form of the artificial neural network (ANN) that is very useful in the field of the machine learning algorithm beyond the statistical models and the regression analysis. To appreciate the capabilities of ANNs to the optimum, researchers have reviewed numerous features such as speed, delay, robustness, efficiency, size, precision, convergence effectiveness, and expansibility. Due to high-speed parallel processing possibilities, ANNs have great potential, so more research in this field should be encouraged. Considering this, ANNs have been applied in areas such as image identification, and natural language processing among other areas. Due to its tolerance to errors, non-linearity, ability to learn from its mistakes, and breakthroughs in relating input and output functions, the capability of solving simple as well as complex problems is present in their design [64], [65].

### 2.1. Background

A brief but surprisingly interesting history of artificial neural networks (ANNs) is that they represent ten years of advances in computing, neurology, and artificial intelligence (AI). ANNs are computing architectures that are inspired by the network in the animal brain. Unlike classical AI systems, they can "learn" and accomplish tasks and look for examples, but they are not programmed with any special rules. It is now high time that some indicators of the development of ANNs are examined, and some of these are as follows see Fig. 1. In 1943, the early concepts of ANNs based on mathematics and algorithms called threshold logic shown in Fig. 2 were created by Warren McCulloch and Walter Pitts, who laid the foundation for future research on neural networks [66]. In addition, in the current year of 1958, the perceptron in Fig. 3 another type of ANN among the more primitive forms was developed by Frank Rosenblatt It is a pattern of algorithms consisting of two layers capable of performing rudimentary functions [67], [68]. Thus, the development of Artificial Neural Networks ANNs as a field can be described as rapidly progressive. Research into ANNs was initially centered on basic perceptron models and multi-layer feedforward networks, despite the existence of other, relatively unchanged network structures.

Although these basic ideas are still invaluable, the work has progressed significantly, and the developments of the last few years are at the core of neural networks. To offer a more up-to-date perspective of the state-of-art, we dedicate additional consideration to the transformer architectures, self-supervised learning, and federated learning that continue advancing the ANNs of the next generation.

1. Transformer Architectures

The transformer architectures have significantly changed the face of deep learning, especially in the natural language processing domain [69]. Unlike the recurrent network like the LSTMs, the transformers employ the self-attention methods which enables the model to attend to different areas of the input sequence at a more efficient way. Unlike RNN and LSTM, the transformer models rid the claim of the sequential data processing thus making them able to tackle long dependency and yield high performance in NLP tasks. Transformers are not just for language-based tasks – Vision Transformers (ViTs) have been proposed and have been categorized to be equally effective as convolutional and recurrent in vision and speech recognition as Speech Transformers. This flexibility has made transformers a useful device in performing tasks that entail structured and unstructured data, thus leading to a paradigm shift in neural network applications across the domains. In addition, the Transformer structure shows unconditional generalizability and does not have a problem with increasing the size of the data in contrast to the recurrent structures; it can be considered one of the most decisive innovations in the recent past, which applies to any task, which implies sequential or structured data.

2. Self-Supervised Learning

Another trend marking further development of ANNs is self-supervised learning (SSL), which minimizes the dependence on massive, annotated data sets. In SSL, the models extract useful representations from huge amounts of data that are not labeled by solving stowed or hidden tasks which in turn enable them to perform well on the final tasks with little supervision. This has been proven to be of great benefit, especially in areas like computer vision and speech processing whereby labeled data is costly and time-consuming to acquire. The recent self-supervised models that include BERT and SimCLR have proved to be extremely good at extracting meaningful representation from the raw data. These are the models that are trained on unrelated data and are later trained with labeled data and the amount of data required to build efficient models is cut short. SSL is changing the paradigm because deep learning can occur even when its applications are unable to easily obtain labeled data, and thus SSL has greatly extended the applicability of neural networks. Impact: The emergence of self-supervised learning holds tremendous potential application in many areas, especially in the carbon copy domains, which are characterized by the lack of data. It can largely contribute to the possibility of scaling AI systems because it doesn't need a lot of labeling, which is more viable for new businesses and new use cases.

3. Federated Learning

Another revolutionary approach that has evolved due to the growing consciousness of data privacy and security is federated learning. Designed as the solution that allows decentralized devices or organizations to learn with each other without sharing raw data, federated learning lets models be trained in different places and does not let data be transferred. This is well explained in areas like health and financial sectors due to the aspects of data privacy that cannot be easily crossed. [64] also, explain more about the developments made in federated learning and demonstrate how the method has grown as a standard to ensure that ANNs are trained in a manner that does not infringe on the privacy of its users. The practice of co-training models while not concentrating on data is becoming crucial as long as the approaches to data protection set tougher requirements. Impact: This means that under the federated learning concept, industries with high privacy demands can still train and offer powerful models in the use of ANNs in areas such as medical diagnosis, personalization of finances, smart gadgets among others.

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4. Other Emerging Trends

- Neural Architecture Search (NAS): NAS minimizes the burden of selecting the architecture of the neural networks as it utilizes automation in arriving at the architecture of the neural networks. Common with many other comparable state-of-the-art models, NAS has played a vital role in determining what efficiency and accuracy are achievable in models.
- Hybrid AI models: Using neural networks with traditional techniques used in artificial intelligence such as rule-based systems or symbolic reasoning is being realized as a way of trying to increase the interpretability of the models while at the same time trying to increase the performance.
- Explainable AI (XAI): As ANN models become more complex, there is a growing emphasis on improving their transparency and interpretability. XAI techniques help explain how models arrive at decisions, making them more suitable for high-stakes applications like healthcare and autonomous systems.

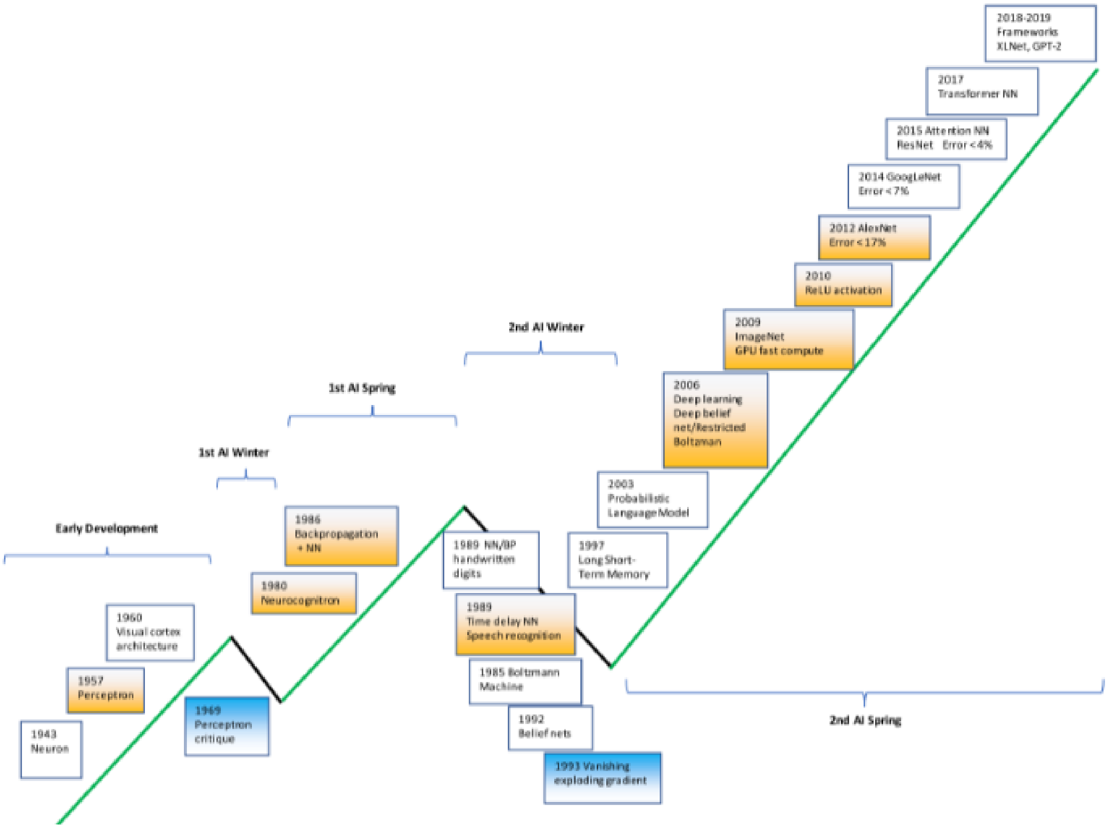


**Fig. 1.** The history of neural networks, [65]

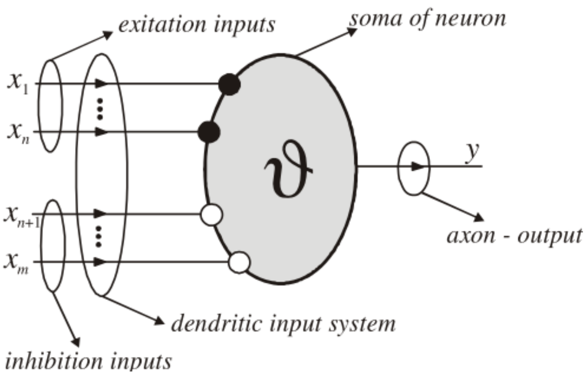


**Fig. 2.** Diagrammatic visualization of McCulloch, [61]

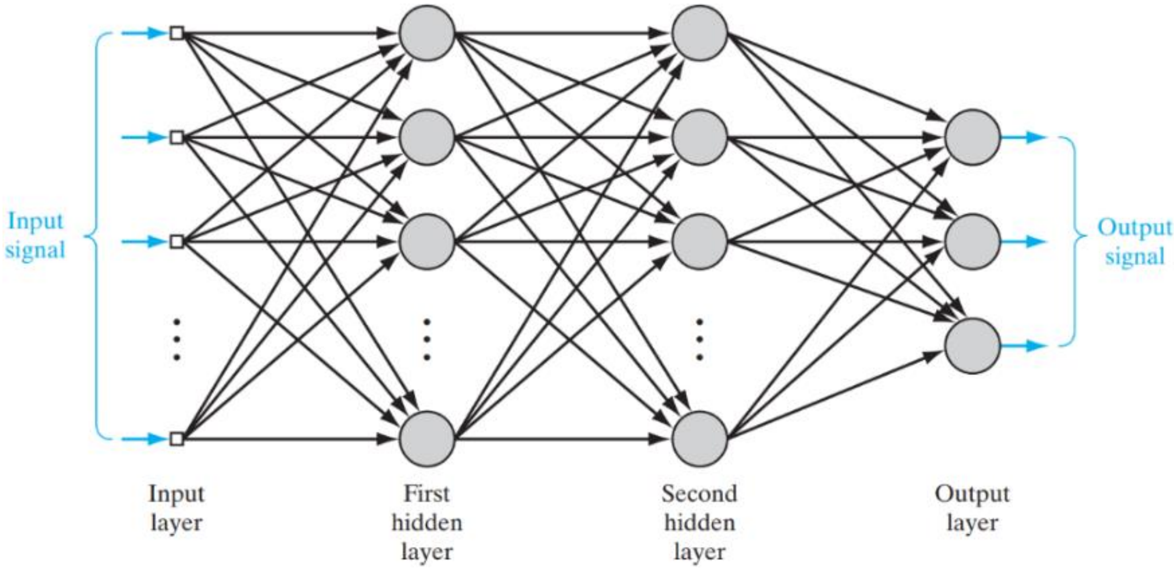


**Fig. 3.** Two hidden layers of perceptron NN, [66]

The basic limitations of perceptrons were highlighted by Marvin Minsky and Seymour Papert in the 1960s by their inability to solve nonlinearly separable problems, which led to a decrease in funding and interest in the study of neural networks. In 1982, the problems of optimization were demonstrated and solved by the Hopfield network, which was introduced by John Hopfield (see Fig. 4), and the backpropagation algorithm was cleared in 1986 by David Rumelhart, Geoffrey Hinton, and Ronald Williams to adjust the weights of connections between layers in a multilayer network, which significantly improved their ability to learn complex patterns Fig. 5 and Fig. 6. This period marked the beginning of the "second wave" of neural network research. More developments were made in ANN architectures, such as recurrent neural network (RNN) creation Fig. 7 and long short-term memory network (LSTM) creation shown in Fig. 8 and Fig. 9, which improved the ability of neural networks to process sequences. In 2006, Geoffrey Hinton and his colleagues introduced the concept of "deep learning", in which neural networks with many layers (deep architectures) are trained using large amounts of data and computing power. Significant progress has been made in a number of AI domains, such as speech recognition, computer vision, and natural language processing, because to this strategy. The breakthrough work in 2012 was the convolutional neural network used by AlexNet in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC), which showed the superiority of deep learning models for computer vision tasks.

### 2.2. Construction of ANN

In recent years, interest has focused on developing and applying ANNs for various machine-learning tasks. The development of ANNs is based on the understanding of the structure and learning mechanisms for the required applications. The layer structure is a critical aspect of ANNs and can vary from a single layer to many layers. The simplest network is a group of neurons arranged in a layer. This configuration is known as a single-layer neural network. There are two types of single-layer networks, namely, feedforward and feedback networks. A single linear neural network (that is, a linear activation function) will have very limited capabilities in solving nonlinear problems because its decision boundaries are linear. The architecture of the ANN consists of three main layers: the input layer, which is the first layer in the network. It receives the input signal to be processed. Hidden layers are between the input and output layers. There can be one or multiple hidden layers. These layers perform most of the computational work of the network through a series of weighted connections, and the output layer is the last layer in the network. It provides the output of the model. The number of neurons in this layer and their activation function depend on the task.

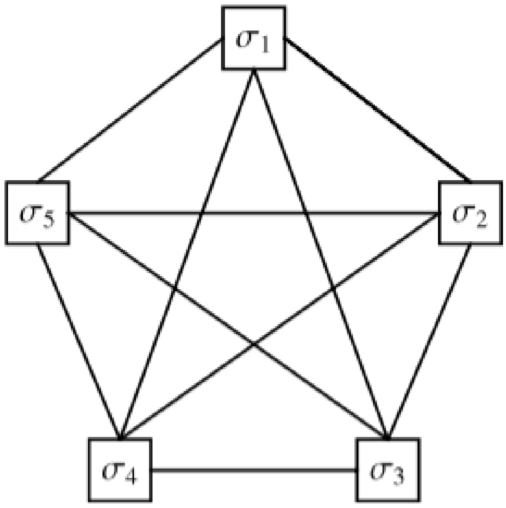


**Fig. 4.** Schematic of the equivalent Hopfield neural network, [67]

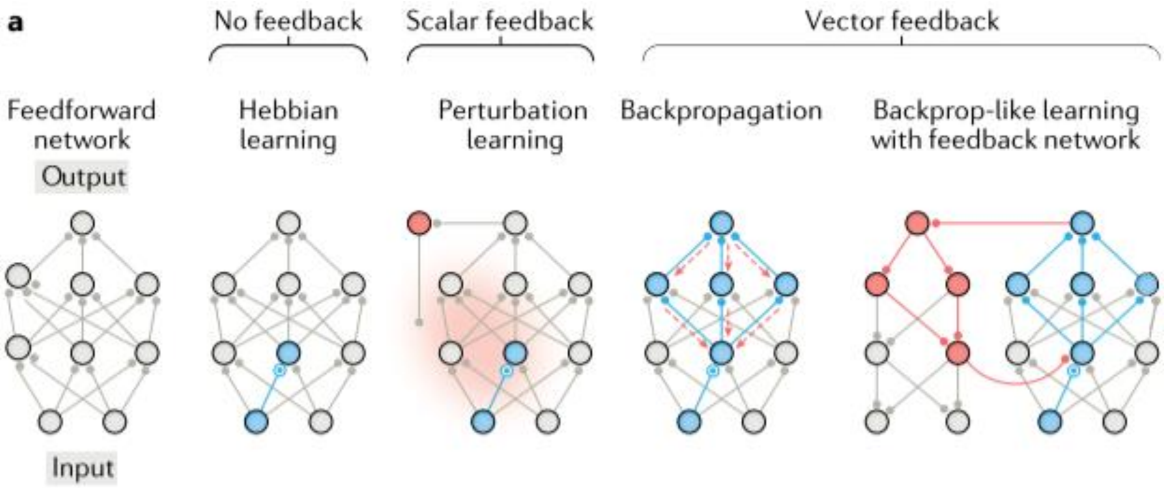


**Fig. 5.** A neural network series of simple computational units [55]

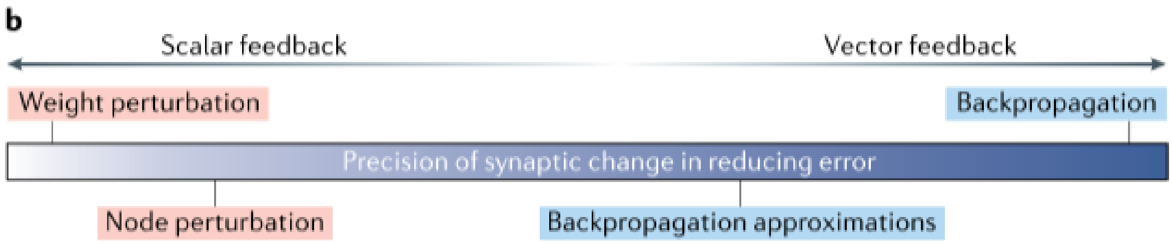


**Fig. 6.** Backpropagation and perturbation algorithms fall along a spectrum with respect to the specificity of the synaptic change they prescribe, [56]

Learning or training neural network models is the method by which optimized weight values are obtained. Learning is aimed at developing the relationship that best fits the general function between the input and output parameters [70]. Neural networks are often trained or altered such that a given input results in a target output that is determined by comparing the output to the target until the output of the network matches the target [71]. Learning can be equated to determining the proper values of the connection strengths that allow all the nodes to achieve the correct state of activation for a given pattern of inputs [72]. The most common cost function used in ANN training is the mean squared error, which is backpropagated through the network during many training iterations (epochs) to achieve the minimum error level. During the training process, the data are typically normalized to ensure that the inputs are within a specific range. However, some studies have adopted a more straightforward approach by ignoring data normalization and instead randomly dividing the data into training, testing, and validation sets [73]. Several parameters are crucial in the design and training of ANNs, including the type of neuron, connectionist architecture, weights, activation function (AF), and training algorithms.

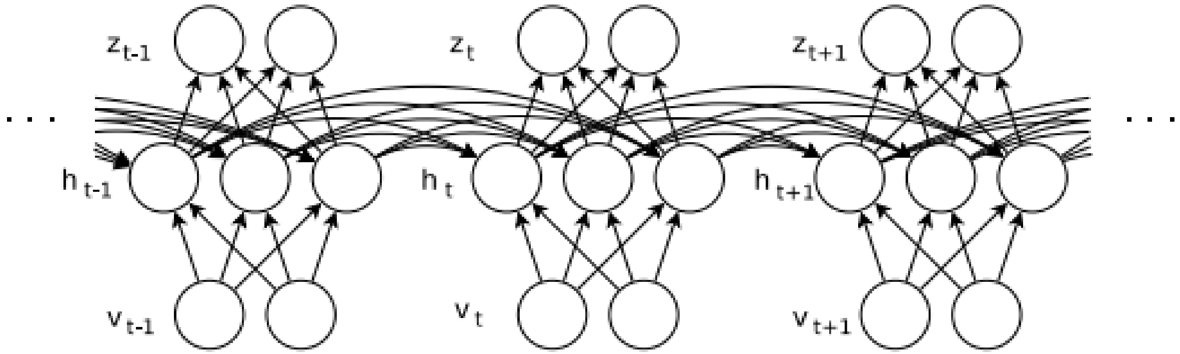


**Fig. 7.** Backpropagation and perturbation algorithms fall along a spectrum with respect to the specificity of the synaptic change they prescribe, [56]

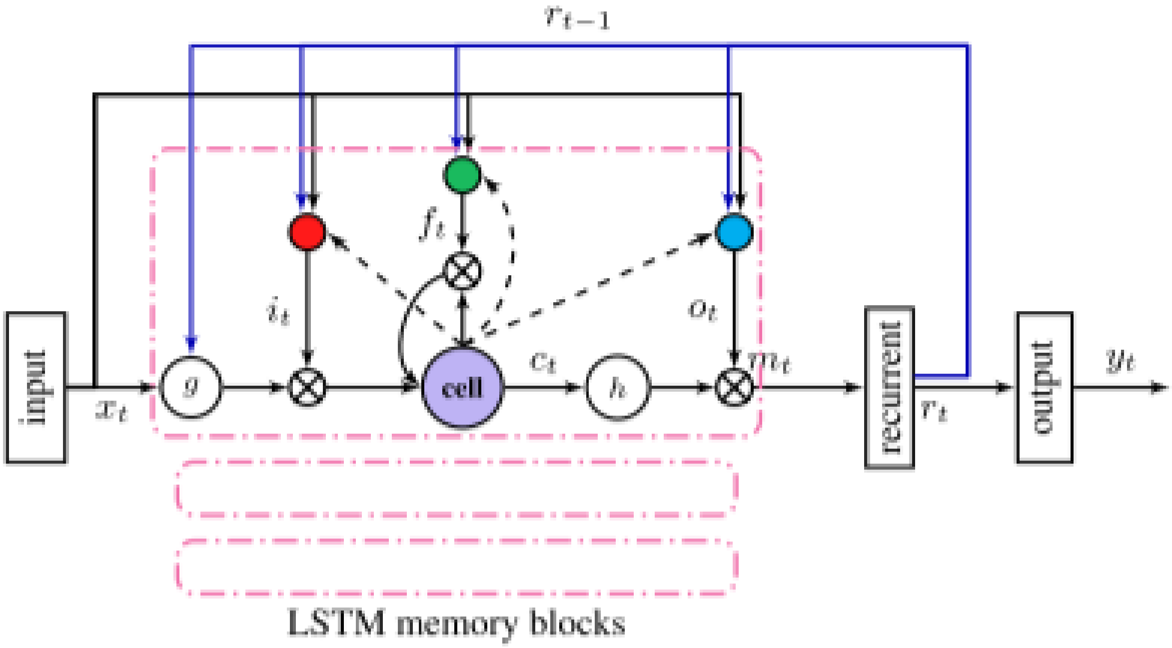


**Fig. 8.** LSTMP RNN architecture. A single memory block is shown for clarity, [57]

### 2.2.1. Neuron

The basis of an artificial neural network (ANN) is an artificial neuron, which performs the same tasks as a genuine biological neuron [74]. The information enters artificial neurons through weighted (weight-multiplied) inputs, which are then added together, skewed, and "processed" using a transfer function. Ultimately, the processed information is transferred via an artificial neuron through its output(s) [75]. The artificial neuron model's benefit is readily apparent in the following mathematical description:

$$\mathcal{Y}(\mathcal{X}) = \mathcal{F}\left(\sum_{i=0}^{m} \mathcal{W}i(\mathcal{X}) \cdot \mathcal{X}i(\mathcal{X}) + b\right) \tag{1}$$

As: $\mathcal{X}i(\mathcal{X})$ is the input parameter in step time $\mathcal{X}$, where $i$ various from 0 to $m$, $\mathcal{W}i(\mathcal{X})$ is the weight value in step time $\mathcal{X}$, where $i$ various from 0 to $m$, b is the bias, $\mathcal{F}$ it's the transfer function, $\mathcal{Y}i(\mathcal{X})$ is the output value in step time $\mathcal{X}$.

McCulloch and Pitts proposed the first mathematical model of a neuron in 1943. It is a binary device with a constant activation threshold, binary inputs, and binary outputs [76]. The following characteristics, which depict its behavior, are often used to characterize an artificial neuron model.

The inputs, or connections, are x1, x2,..., xn. A single input to the neuron, known as a bias, has a constant value of 1. It is often represented as a distinct input, say x0, but for the sake of simplicity, it is handled here as an input set at a constant value. Each input connection has an associated weight: $w_1$, $w_2$,..., $w_n$.

Functions of input $\mathcal{F}$: Determine the neuron's combined net input signal.

$$\mathcal{U} = \mathcal{F}(\mathcal{X}, \mathcal{W}) \tag{2}$$

The neuron's activation level is determined by the activation (signal) functions.

$$a = s(u)$$

The output function calculates the value of the signal that the neuron emits (the axon), o = g(a); the output signal is often taken to be similar to the neuron's activation grade, that is, o = a.

There are different types of neurons, such as fuzzy neurons and fuzzy networks [77], which are described by fuzzy control and artificial neural network methodologies in the form of an analytical formula instead of a common fuzzy rule table. Oscillatory neurons and oscillatory neural networks [78] were used to analyse the Wilson and Cowan neural network model by revealing bifurcation dynamics and predicting behavioural changes based on parameter variations. Perceptron type [79] studied the implementation of binary AND and EXOR gates using artificial neural networks, utilizing perceptron's and threshold elements for neuron output functions.

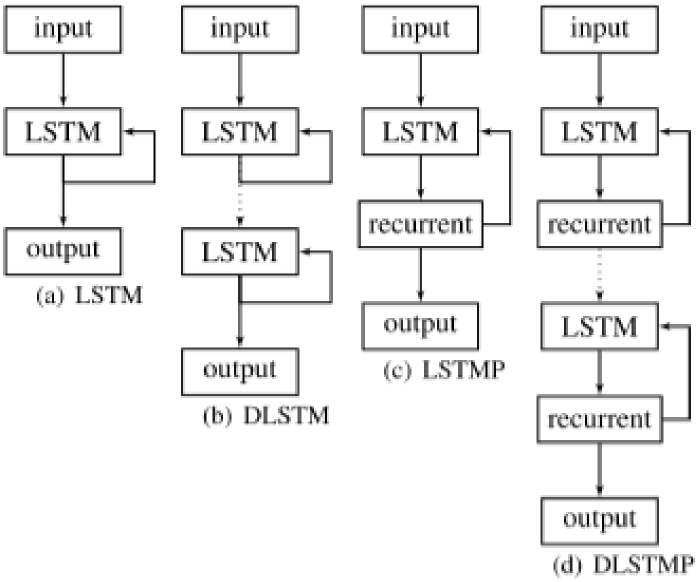


**Fig. 9.** LSTM RNN architectures, [70]

### 2.2.2. ANN Architecture

An artificial neural network is created by joining many artificial neurons. The topology, architecture, or graph of an artificial neural network refers to the way that several artificial neurons are connected. Different topologies of neural networks may be utilized to estimate any nonlinear function since they are employed as universal function approximators. In addition to the layers of neurons that are employed, connectionist architectures may be divided into groups according to the quantity of input and output neurons. carried out by the later-layer neurons. Taking into account the characteristics of neurons, their connections, and the composition of their layers, the primary designs of artificial neural networks may be categorized as follows: recurrent networks, multilayer feedforward networks, and single-layer feedforward networks

### Single-Layer Feedforward Architecture

A feed-forward artificial neural network (ANN) is distinguished by a feedback-loop-free, unidirectional information flow from input to output. The quantity of connections between neurons, the kind of transfer functions that each neuron uses, and the total number of layers are all unrestricted. Only linearly separable problems may be solved by a single perceptron, the most basic type of feed-forward artificial neural network. This artificial neural network has just one input layer and a single neural layer, which is known as the output layer [80].

The information always transforms in a single direction (thus, unidirectional), which is from the input layer to the output layer. Fig. 10 displays how the number of network outputs and the number of neurons in networks built using this architecture are always equal. These networks are typically used to solve linear filtering and pattern classification issues. Adaline neural network is an example of a single-layer feedforward design. The dot product of input x and the weight vector w constitutes the only output of the single-layered neural network Adaline, which has N inputs. [81].depicts a single-layer feed-forward neural network (completely linked). This structure consists of two levels, one being the input layer. Nevertheless, since no computations are done in the input layer, it is irrelevant. The weights transfer input signals to the output layer, where the neurons calculate the output signals [82].

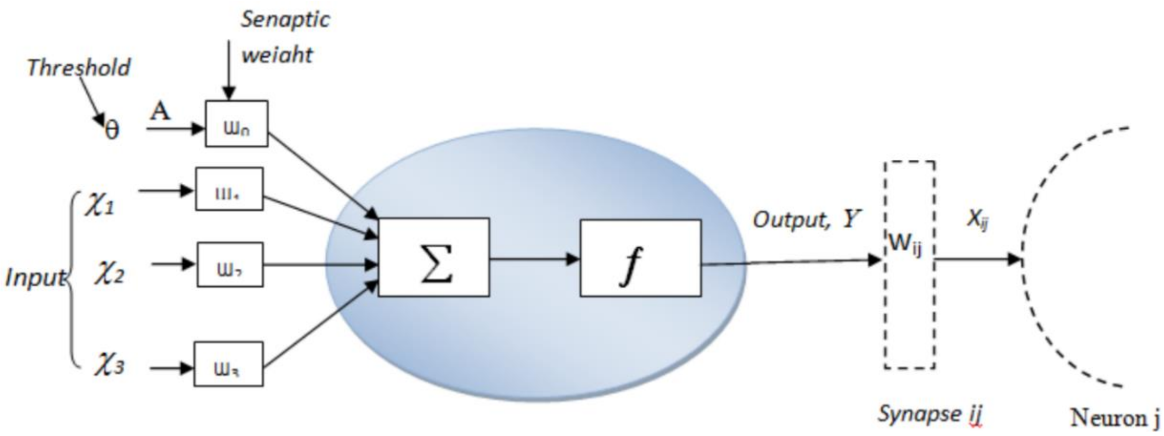


**Fig. 10.** Simple Artificial Neural Network, [80]

### Multiple-Layer Feedforward Architectures

Unlike networks according to the preceding design, feedforward networks including many layers possess one or more neural layers that are concealed. An FNN is an updated ANN structure that can solve complex and linear problems due to the introduction of a hidden layer between the input and output layers [83]. FNNs are computational type that consist of several neurons (nodes) that are connected using synaptic links (weights) and are arranged on a layer-by-layer basis. Thus, FNNs have a specific structural configuration (architecture) in which the nodes at a layer have forward connections from the nodes at its previous layer [84] Enhancing the computational power of the system can be achieved by incorporating 'hidden' nodes, which are neither input nor output nodes. This method is akin to expanding the system's set of variables by introducing new dependent variables [85]. The mammalian visual system is among the best-studied instances of feedforward excitation. Signals originate from photoreceptors, travel via bipolar cells, retinal ganglion cells, lateral geniculate nucleus (LGN) relay neurons, layer 4 primary visual cortical (V1) neurons, V1 neurons in other layers, and neurons in higher cortical areas [86].

**Recurrent artificial neural networks**

A recurrent artificial neural network is a recurrent artificial neural network with recurrent topology. Recurrent neural networks are feedforward neural networks extended by the addition of edges that span adjacent time steps, giving the concept of time to the model [87]. It is like the feedforward neural network with no restriction concerning back-loops. In these situations, information is no longer transmitted only in one direction; rather, it is also transmitted backward. The architectures of recurrent networks range from fully interconnected to partially connected networks, including multilayer feedforward networks with separate input and output layers. It's important to note that fully connected networks lack distinct input layers, as each node receives input from all other nodes [88]. A recurrent neural network (RNN) consists of an input layer, a single hidden layer, and an output layer. The input layer includes external inputs and feedback signals from the RNN's output. The hidden layer, containing (N) neurons, is activated by a nonlinear function to replicate all system nonlinearities [89]. The output of the neural networks is expressed by

$$y_{nn} = w_1 h_1 + w_2 h_2 + \cdots + w_N h_N = \sum_{i=1}^{N} w_i \, h_i \tag{3}$$

where $w_i$ are the weights between the hidden layer and the output, $h_i$ are the responses of the neurons at the hidden layer and $N$ is the number of neurons.

The neuron response is expressed by

$$h_i = h\left(\sum_{j=1}^{M} w_{ji} \, x_j\right); i = 1 \dots N \tag{4}$$

where $xj$ are the inputs, $wji$ are the weights between the inputs and the neurons at the hidden layer, $M$ is the number of inputs, $N$ is the number of neurons and $h$ is the activation function.

Elman neural networks (1990) define as partial recurrent networks or simple recurrent networks; these are MLPs extended with one or more extra structure layers that store the output values of one of the layers postpone by one step [90]. The LSTM and GRU networks are two major variants of recurrent neural networks (RNNs). Compared to traditional RNNs, LSTM and GRU networks effectively mitigate gradient vanishing and exploding issues, enhancing the model's long-term memory capabilities. This improvement allows for deeper RNN architectures, ultimately boosting model performance [91], [92] studied the construction of recurrent neural networks (RNNs) inspired by biological neural network (BN) topology. [93] suggested a new recurrent ANN model based on a multiplicative neuron model. The offered model is called the recurrent multiplicative neural artificial neural network model (RMNM-ANN) see Fig. 11. [94] examined the effectiveness of a recurrent neural network in processing image metrics to detect delivery errors early during treatment. The median segment index for error detection was 66 out of 180, with no false positives.

### 2.2.3. Activation Function

An artificial neural network's activation functions are essential components since they have a rule for learning and provide a feeling of complex and nonlinear mappings between the inputs and outputs [95]. The activation function endows deep neural networks with authentic artificial intelligence [96], [97] discussed different activation function types.

Linear Activation Function.

Considering the simplest example of a linear equation, the equation output can be equivalent to the input. As shown in Fig. 12.

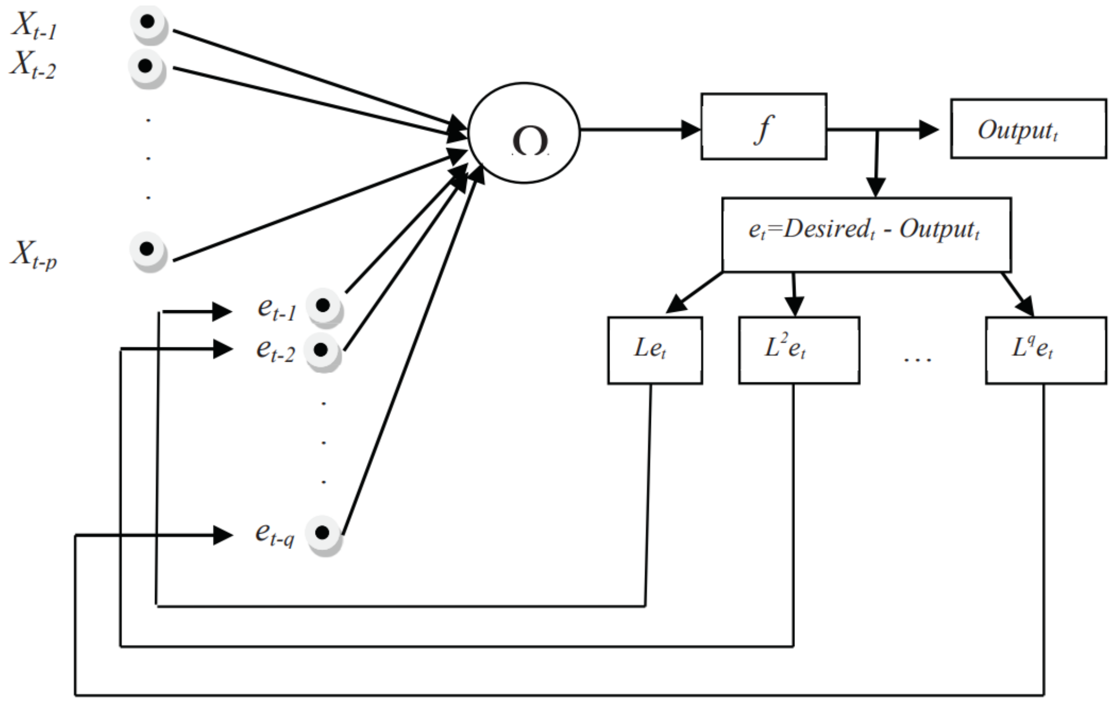


**Fig. 11.** RMNM-ANN model, [94]

$$\mathcal{F}(\mathcal{X}) = a\mathcal{X} \tag{5}$$

Sigmoid Activation Function.

It is one of the most used activation functions. See Fig. 13.

$$\mathcal{F}(\mathcal{X}) = \frac{1}{1 + e^{\mathcal{X}}} \tag{6}$$

Sigmoid Symmetric Activation Function.

The symmetrical sigmoid activation function is the usual tanh sigmoid function with an output between minus one and one. Shown in Fig. 14.

$$\mathcal{F}(\mathcal{X}) = \tanh(a\mathcal{X}) = \frac{2}{1 + e^{-2\mathcal{X}}} - 1 \tag{7}$$

Soft sign Activation.

Soft sign is one of the most important functions and is smoother than the tanh activation function.

$$\mathcal{F}(\mathcal{X}) = \frac{\mathcal{X}}{1 + |\mathcal{X}|} \tag{8}$$

ReLU Activation Function.

The most common type of nonlinear activation function in neural networks is called ReLU, or rectified linear unit. One benefit of utilizing the ReLU function is that it allows for partial neuron activation. This indicate that a neuron will only become inactive when the linear transformation's output is zero [95]. See Fig. 15.

$$\begin{gathered} \mathcal{F}(\mathcal{X}) = 0\,, \mathcal{X} \leq 0 \\ \mathcal{F}(\mathcal{X}) = \mathcal{X}\,, \mathcal{X} > 0 \end{gathered} \tag{9}$$

Leaky ReLU Activation Function.

Leaky ReLU is an extension of the ReLU (Rectified Linear Unit) activation function where for negative values of x, instead of defining the ReLU functions' value as zero, it is defined as an extremely small linear component of x [95]. See Fig. 16.

$$\mathcal{F}(\mathcal{X}) = .01\mathcal{X}\,, \mathcal{X} < 0$$
$$\mathcal{F}(\mathcal{X}) = \mathcal{X}\,, \mathcal{X} \geq 0 \tag{10}$$

The scientific community has recently become more interested in studying activation functions that are trainable, learnable, or adaptable—that is, activation functions that can be learned during the learning process [98]. An inappropriate selection of the activation function for the neural plant can lead to the loss of information of the input during forward propagation and the exponential vanishing/exploding of gradients during back-propagation [99]. Unfortunately, there is no way to determine the appropriate function analytically, and the optimal activation function is generally determined by trials or tuning [100].

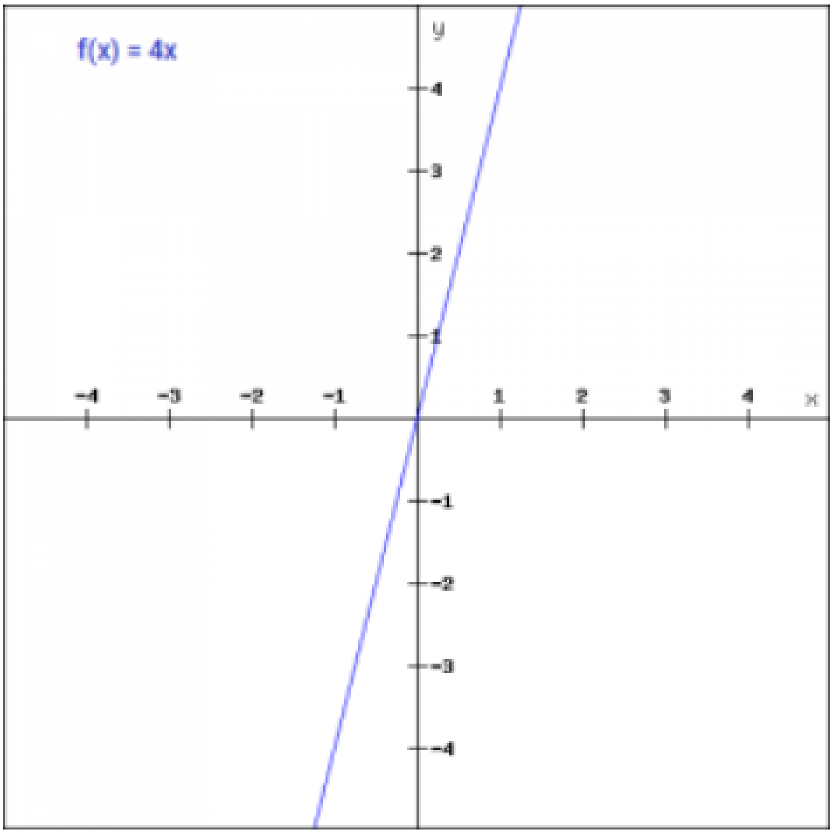


**Fig. 12.** Linear activation function, [96], [98]

### 2.2.4. Learning Algorithm

Artificial neural networks' tendency to learn from sample presentations, or patterns, which mirror system behavior, is one of its fundamental features. The network can now generalize solutions since it understands the relationship between inputs and outcomes. This indicates that for each given input value, the network can produce an output that nearly matches the intended or expected output. For a particular issue and network architecture, the training performance varies with respect to the goal function and underlying error surface [101].

Learning algorithm types:

- Supervised learning

Supervised learning involves using known output values for a given set of input signals. In other words, each training sample includes input signals along with their corresponding outputs. To facilitate this process, an input/output data table—also known as an attribute/value table—is necessary. Neural structures then derive a hypothesis about the system being learned based on this information [102].

- Unsupervised learning

The neural network learns certain intrinsic properties of the entire set of all the input vectors that are offered to it; only vectors that are given are x. Two types can be distinguished further among modern unsupervised algorithms: Irrespective of whether it is competitive or not [103].

- Reinforcement learning

Reinforcement learning is a machine learning technique that adjusts the parameters of an artificial neural network. Unlike traditional supervised learning, where data is provided, reinforcement learning generates data through interactions with the environment. Its focus is on determining how the neural network should take actions within an environment to maximize long-term rewards. This approach is commonly integrated into artificial neural networks' overall learning algorithms [75].

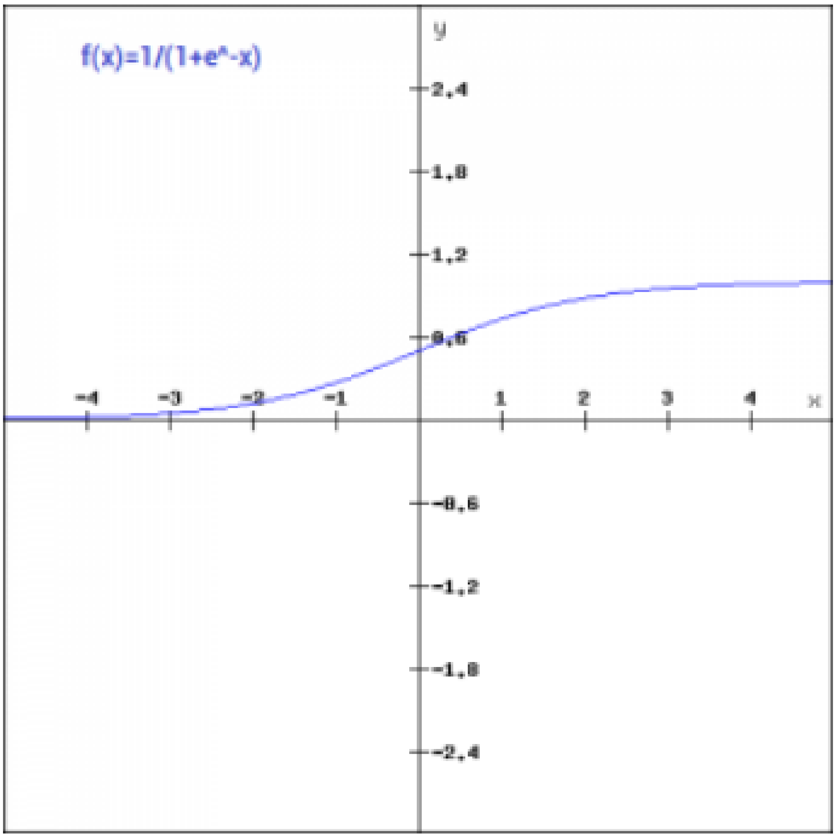


**Fig. 13.** Sigmoid Function, [96]

## 3. Optimization Techniques for ANN Hyperparameters

In the pursuit of optimizing Artificial Neural Networks (ANNs), selecting appropriate hyperparameters such as learning rate, batch size, and the number of hidden layers is critical for maximizing model performance. The manuscript initially discussed traditional methods such as grid search and random search, both of which, while reliable, come with several limitations. These methods tend to be computationally expensive, especially for high-dimensional search spaces, and may miss optimal configurations due to their limited exploration capabilities.

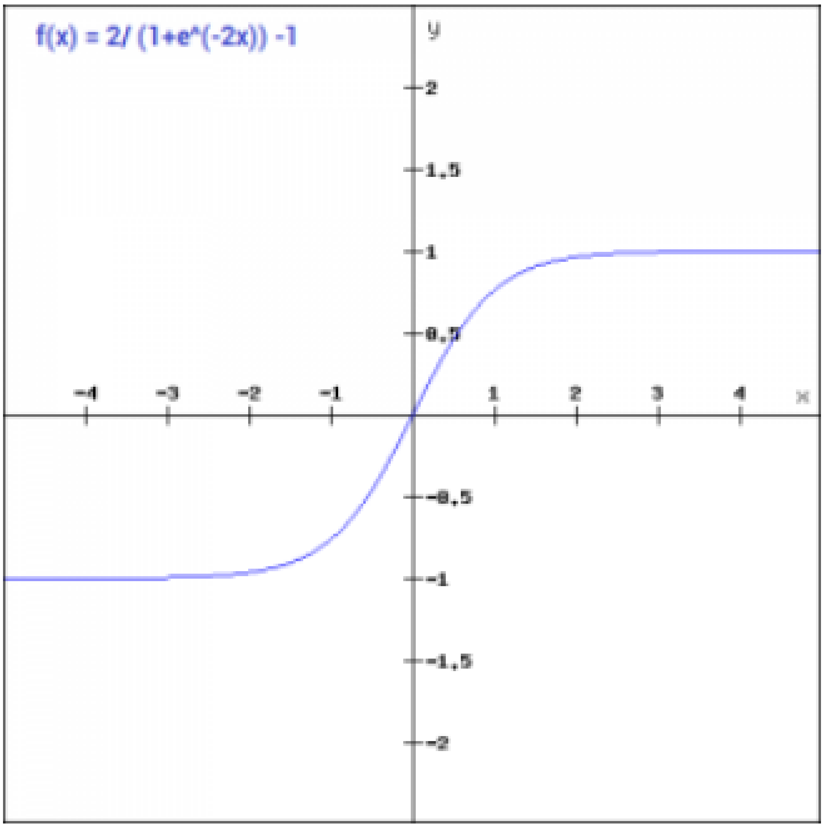


**Fig. 14.** Tanh Function, [96]

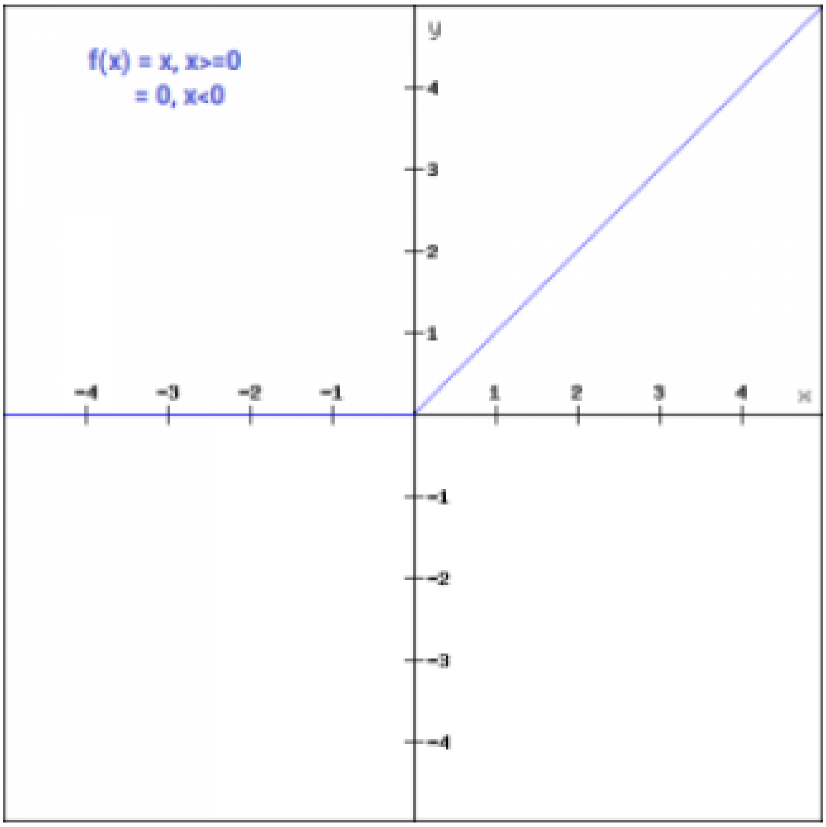


**Fig. 15.** ReLU Activation Function plot, [96]

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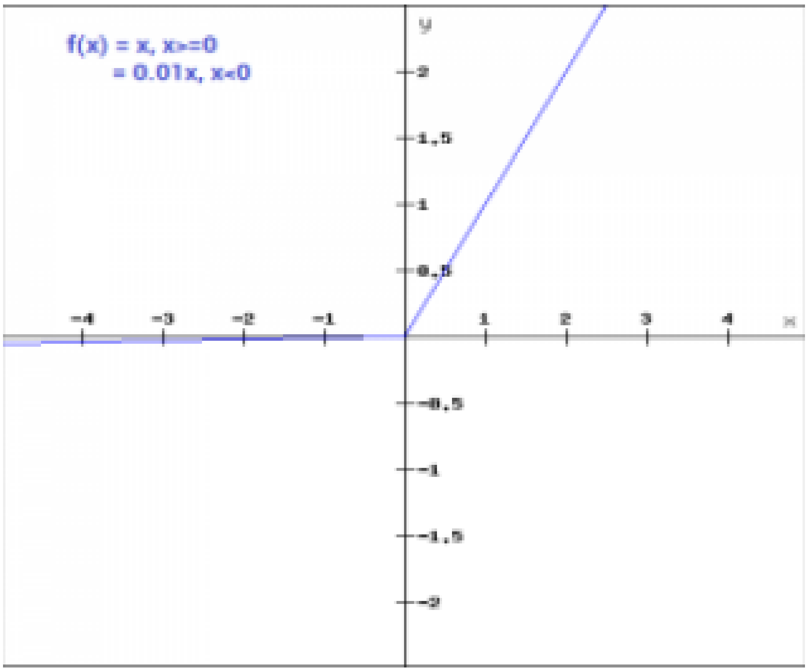


**Fig. 16.** Plot of Leaky ReLU function, [96]

1. Bayesian Optimization

Bayesian optimization has emerged as a more efficient alternative for hyperparameter tuning. It applies a probabilistic model to predict the performance of different hyperparameter configurations, updating its beliefs as more information is gathered. This method enables more targeted exploration of the search space, significantly reducing the number of evaluations required compared to grid or random search. In fact, studies have shown that Bayesian optimization outperforms traditional methods in both speed and accuracy, making it highly suitable for complex ANN models [104].

Advantages:

- Less frequent therefore less work is done on them, especially for those models that are more resource-demanding.
- Kind of search that adapts to the exploration of the promising areas in a hyperparameter space.
- Most beneficial for the models with large numbers of hyperparameters and when the evaluation of the function is computationally costly.

2. Genetic Algorithms

Genetic algorithms (GAs) – another modern approach which is based on principles of natural selection is also used for hyperparameters optimization. The need for modeling concerns GAs, which are a population-based search, in which hyperparameter sets or individuals proceed through crossover, mutation, and selection processes over generations. Based on this evolutionary perspective, GAs can then search over a wider domain and obviate local optima, and thus improve on the overall optimization.

Advantages:

- Global search strategy which is useful for moving away from local optimum.
- Speed of the search that makes it possible to vary in hyperparameter space almost in any way.
- This method is more suitable when one wants to overcome multiple hyperparameters at the same time and for deep learning architectures as well.

3. Automated Machine Learning (AutoML)

AutoML systems assist in the selection of models, choice of hyperparameters, and even feature engineering; using AutoML for improving ANN is therefore possible. AutoML frameworks like Auto-Keras or TPOT look at multiple hyperparameters and the different architectures and decide which is most competent in providing the most results required. AutoML helps to minimize the involvement of an expert and can definitely cut down the duration of the model making process.

Advantages:

- Strong automation of processes which helps to handle hyperparameters adjustment without a need for an expert.
- Can do both the selection of the structure of the model and the selection of the parameters of the model at the same time.
- Optimizes the general functioning of the program through the use of two strategies namely Bayesian optimization and random search.

## 4. Practical Implementations of ANNs: Bridging Theory and Application

Most ANNs are based on mathematical neuron models, activation functions and learning algorithms Essentials about ANNs' functioning, although vital, are most effective when used to solve real-life problems. In order to offer more substance and prove that these advancements were successfully applied, we further illustrate the examples with real-life case studies taken from the field of industry applications of artificial neural networks.

1. Healthcare: Diagnosis and Imaging in Medicine

Case Study: CNN-based Tumor Detection. In healthcare, ANNs specifically CNNs have radically disrupted some of the most important areas of medical imaging. For instance, CNNs are applied in identifying tumors in magnetic resonance imaging (MRI) as well as the X-ray. A much quoted one encouraged a CNN to be trained on thousands of labeled MRI scans to accurately detect tumors. The model fared better with the conventional diagnostic techniques, as it also identified apoptosis at an initial stage that was not recognizable by radiographers. Practical Impact: CNNs diagnose with greater accuracy meaning few false positives or negatives are made and improve patient outcomes by allowing early detection of diseases such as cancer among others.

2. Finance: Credit Score and Fraud Check

Case Study: Application of RNNs in finance, where Recurrent Neural Networks (RNNs) are widely used to detect fraudulent transactions. RNNs are capable of modeling temporal dependencies of sequences of transactional data that can be used in an attempt to identify patterns that can be indicative of fraud. They applied RNNs in a global financial institution to track credit card transactions in real-time and the results showed that the cases of fraud were cut by up to 30% when compared to rule-based systems. Practical Impact: ANNs help to enhance the means of fraud identification and at the same time decrease the number of false positives thus protecting the customers and saving the financial institutions millions of dollars in fraud prevention.

3. Automotive: Autonomous Driving

Case Study: Self-Driving Cars Using Deep Learning Therefore, Deep Neural Networks (DNNs) have been at the heart of autonomous vehicles for tasks such as object recognition, path planning, and decision making. Today's companies like Tesla and Waymo apply deep learning architectures to let vehicles process visual data from cameras and LiDAR sensors to distinguish pedestrians, other automobiles, and road signs. As an example, in one case, deep learning models were trained on millions of images taken from on-road cameras with the aim of fully autonomous driving without any intervention from the human driver. Practical Impact: The use of DNNs in self-driving helps to reduce risks on roads as compared to human beings who are behind the wheel, and one of the leading causes of accidents.

4. Retail: Personalized Recommendations

Case Study: Application of multi-layer perceptron in E-Commerce The multi-layer perceptron is in demand in the retail industry to provide product recommendations to the e-shopping customer. For example, Amazon uses MLPs to predict what a specific customer prefers to buy, what he/she has previously purchased, and other characteristics of products that may be interesting to the user. Such systems handle massive data sets and utilize MLPs to identify concealed patterns in consumers' behavior. Practical Impact: The ANN-based recommendation system motivates enhanced sales, effective user interaction, and optimum customer satisfaction due to its efficient ability to provide the most suitable choice of products according to the consumer's specific preferences.

5. Energy: Predictive Maintenance in Power Plants

Case Study: Application of ANNs for Predictive Maintenance of Power Plants and Energy Companies Turbines and generators that are essential in power plants and other energy companies are today being monitored through ANNs for their prediction maintenance. By using ANN models to train with the historical data of the sensors, energy companies will be able to determine when a machinery is likely to fail before it does so therefore maintenance can be done appropriately. One of the large utility companies adopted the ANN system that forecasted the failure of the turbines with 85% accuracy helped in decrease unpredictable downtime and brought down the repair cost to millions. Practical Impact: The performance of ANNs in predictive maintenance optimizes energy generation, cuts down on costs and expenses, and reduces the amount of time equipment lasts before it needs replacement most of which is costly.

6. Natural Language Processing: Chatbots and Language Translation

Case Study: Transformer Models for Language Translation In the field of natural language processing, transformer models have emerged as the go-to solution for different undertakings such as language translation and chatbot solutions. For example, Google's BERT model is a transformer-based network that changed the horizon of language understanding by performing required computations in terms of entire sentences or paragraphs rather than words. This makes BERT grasp the context and other details of human language and leads to better translation as compared to other models. Practical Impact: Transformer-based models can translate languages with better and more fine-grained understandings to break physical barriers of communication and improve the general human-computer interaction in use cases such as Virtual Personal Assistants and chatbot customer services.

## 5. Challenges and Limitations of ANNs

While Artificial Neural Networks (ANNs) offer powerful tools for modeling complex, nonlinear relationships, several inherent challenges must be acknowledged to ensure a balanced understanding of their applicability: While Artificial Neural Networks (ANNs) offer powerful tools for modeling complex, nonlinear relationships, several inherent challenges must be acknowledged to ensure a balanced understanding of their applicability:

1. Overfitting

Through overfitting the ANN model acquires techniques for picking out noise and patterns in the training exercises and performs very well in the training set but very poorly in a new set. This is often the case with, deep learning models that are characterized by a large number of parameters; this makes them train more by memorizing the data than generalizing it.

Mitigation: To mitigate this, several measures can be recommended; these include the use of Regularization such as L1/L2, Dropout, Early Stopping, as well as Cross-validation. Further, dividing the training set into a training set and a validation set assists in checking the model's generalization performance during the training phase to produce reliable models. Further studies should be directed to the adaptation of these techniques for enhancing model robustness in situations with inadequate data.

2. Large and Diverse Datasets

ANNs are sensitive to the input data and the larger the diverse and quality data sets the better the performance of the models. Due to this, ANN systems would need large amounts of data to incorporate into the computational models with emphasis on the interactions between the input variables and the output predictions. In that case, getting such datasets can be challenging and will require a lot of time, especially in niche areas like health, or companies handling personal data. In addition, models trained in lack of or inadequate data may be inclined to develop bias or ineptitude in making estimations in diverse real situations. Mitigation: Data augmentation, transfer learning, and synthetic data generation are some of the strategies that can be used to handle the issue of data scarcity. Also, the use of frameworks such as active learning—where the model determines which samples are most important for labeling can help alleviate the sampling of large data sets while guaranteeing model robustness in different conditions.

3. Computational Resource Requirements

Another drawback of the ANN models, especially the deep learning architectures is that their training involves the use of a lot of computational resources, thereby consuming a lot of processing time and memory. This is particularly the case in models having many parameter values, for like CNNs or RNNs that would take days and even weeks to train on normal computers. The requirement of high-performance hardware of GPU, TPU or etc could become a big issue for the researcher or organization who do not have much access to such hardware infrastructure. Mitigation: There are different approaches to reduce computational costs like pruning, quantization and knowledge distillation which really reduces the complexity of the model with acceptable performance. Further, there are options in cloud computing platforms and distributed training to overcome some of the above drawbacks of inadequate hardware. Future studies need to investigate ways of improving the structure of ANNs, which would suppress the number of computations needed in classification.

4. Interpretability of Models

They are, however, not as interpretable and are widely described as black-box models because of this feature. In more elaborate architectures with several millions of parameters, it is difficult to comprehend how the network achieves certain decisions. This lack of transparency becomes an issue in fields like medicine, money, and law because the ability to comprehend how the model works as well as trusting its output is important. It is important for stakeholders and end-users to explain model forecast to produce an element of transparency as well as improve decision-making. Mitigation: New approaches have been applied to enhance the concerns related to the interpretability of the ANNs which are known as Explainable AI (XAI) techniques these include LRP (Layer-wise Relevance Propagation), SHAP and LIME. These tools assist in making the outputs of the ANN more interpretable by giving an insight into the features that contributed most to ANN's decision. Thus, there is a need to advance nothing for the actualization of XAI methods related to ANN models.

## 6. Ethical and Societal Implications of ANN Deployment

Considering this, one should look for the moral and social impact of the ANNs as the networks spread across the community aspects, including such priorities as healthcare, financial, and surveillance networks. When deployed ANN can certainly shift these industries by enhancing efficiency and decision-making however the issues that come across with ANN need to be managed to be able to guarantee the usage of the technology benefits the industry and lessens the

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losses. This section highlights several key ethical concerns: This section discusses some of the important ethical issues namely:

1. Privacy and Data Security

Concern: The ANN models particularly those applied in health and financial-related sectors rely on massive input of-sensitive data to make decisions and predictions. Such information may include individual's health information, their financial transactions, and communication in formats that may be vulnerable and hawked. Like in surveillance systems, the use of ANNs also leads to a violation of privacy since data is collected without permission. Implication: To maintain confidence in ANN technologies, it is necessary to apply a high level of data protection and policies that acknowledge standards like the General Data Protection Regulation (GDPR) or those like it. That's why while acquiring and processing personal data, methods of masking and encoding must be used, and a clear procedure for using the data must be established so that people cannot be identified. Privacy and Data Security:

2. Bias in Decision-Making

Concern: Here, we have to consider that ANN models are trained on a historical dataset and generally, datasets are not devoid of bias. These biases can result in discrimination, especially in areas like health and finance. That is, biased data can cause ANNs to reject credit to certain demographical strata or misdiagnose diseases given affected medical information. ANN models implemented in criminal justice and surveillance might increase racial or socioeconomic prejudice and in turn, prejudice is privileged against a disadvantaged group. Implication: It is crucial for developers to carefully clean the data from the training sets for signs of dataset biases and it is necessary to state that ANN should not amplify the existing disparities but combat them instead. The problem of bias in decision-making should be solved using tools such as fairness-aware machine learning and bias mitigation algorithms. Furthermore, more transparency must be implemented in the model so that accountability and supervisory capacities can be provided. Lack of Transparency and Accountability:

3. Societal Consequences

Concern: ANNs, especially deep learning models are usually described as black-box systems because of their low explicability. This lack of transparency means something that users, regulators, or even developers cannot easily explain. In sectors such as health, this situation creates ethical problems, where human healthcare givers are unable to justify why an ANN came up with a certain diagnosis or recommendation. Implication: Improving the model interpretability which can be achieved by, for instance, taking measures like Explainable AI (XAI) needs to be achieved to ensure the users trust the ANN systems. Moreover, there should be a definite channel of responsibility whenever they provide decisions, more so, based on the ANN models in life-related scenarios. There is a STATE that ANN has to provide guidelines for reviewing the decisions taken and the integration of human intervention. Ethical Use in Healthcare:

## 7. Engine Variables and Performance Parameters

Engine performance is a sign to which degree of success its assigned job is done, i.e., the conversion of the fuel chemical energy into the required mechanical work. The prediction of the engine performance effective parameters like exhaust gas temperature, specific fuel consumption, power, torque and thermal efficiency under different engine variables like compression ratio, injection timing and duration, fuel type, engine load, and speed on engine performance can be investigated experimentally and then modelled by using ANNs without needing explicit physical equations. This capability enables the optimization of engine design and operation for improved efficiency, even when using alternative fuels or adjusting operating conditions. The integration of ANNs into engine testing and design processes represents a significant advancement in engine technology, offering a powerful tool for enhancing engine performance and environmental sustainability.

### 7.1. Performance Criteria

The effective engine performance parameters are power, mechanical efficiency, indicated mean effective pressure, torque, volumetric efficiency, air-fuel ratio, brake-specific fuel consumption, and thermal efficiency.

Power and Mechanical Efficiency.

$$ME = \frac{B.P}{I.P} \tag{11}$$

$$I.P = \frac{P_{mi}\ L\ A\ n\ K}{60}\ (Watt) \tag{12}$$

As n is the total number of cylinders, $P_{mi}$ is the mean effective pressure, L is the length of the stroke, A is the surface area of the piston, and k is a constant.

$$B.P = \frac{2\pi NT}{60}\ (Watt) \tag{13}$$

Brake effective pressure and torque.

The brake means effective pressure.

$$B_{m.e.p} = \frac{2\ B.P}{ALNn} \tag{14}$$

Frictional mean effective pressure.

$$F_{m.e.p} = I_{m.e.p} - B_{m.e.p} \tag{15}$$

Volumetric efficiency

$$\eta_v = {}^{V}\!/_{Vs} \tag{16}$$

V = volumetric of air intake,

Vs = swept volume

Air/fuel ratio.

It is the air mass ratio to the mass of fuel in the air/fuel mixture.

The relative air/fuel ratio is the ratio of the actual air/fuel ratio to the stoichiometric air/fuel ratio required to burn the total fuel supplied.

Specific fuel consumption (S.F.C.).

It is the total fuel mass consumed per kW produced per hour and is a standard of economic power production.

Thermal efficiency.

$$\eta_{th} = \frac{I.P}{mf\ * C} \tag{17}$$

$m_f$ = fuel mass used in kg/sec,

C = the calorific value of fuel (lower)

## 8. Engine Performance of a Hydrogen/Gasoline

The fast expansion of industrialization and growing human population have almost consumed fossil fuel reservoirs and negatively it has affected on the environment, Which has pushed researchers to investigate a new, clean, renewable and alternative fuel sources for internal combustion (IC) engines. The hydrogen is promising as second fuel for IC engines, but it has a high autoignition temperature make it more suitable to be used in spark ignition (SI) engines than the use of it in compression ignition (CI) engines. The mixing of gasoline and incoming air due to the great laminar flame and excessive diffusion speed and this leads to increase the homogeneity of the total combustion of the mixture. This mixture delivers better performance compared to that of single fueled engines. The performance characteristics of a hydrogen–gasoline dual fuel engine is determined basically by the design parameters and operating condition. The effects of engine variables like the engine speed, engine load, spark timing, hydrogen/gasoline blending ratio and excess air ratio on the performance characteristics were investigated.

### 8.1. Engine Speed

The speed of the engine is one of the most influential variables on engine performance. [105]-[107] For a single-cylinder SI engine, the effects of engine speed under various hydrogen mass fractions were examined in terms of the BMEP, volumetric efficiency, braking power, thermal efficiency, mechanical efficiency, and brake thermal efficiency. Fig. 17 shows how the BMEP varies with engine speed under typical circumstances. At 3000 rpm, the BMEP decreased by 0.64 and 1.28 (bar) when 10% & 20% hydrogen mass fractions were added, respectively. The effect of adding hydrogen on BP is shown in Fig. 18. The change of the mechanical efficiency indicated thermal efficiency, volumetric efficiency, and brake thermal efficiency see Fig. 19. Increasing the speed has a high influence on volumetric efficiency since a higher speed decrease the time required for the exhaust stroke, resulting in a decrease in the intake length, which leads to a decrease in volumetric efficiency which leads to a reduction in the BTE as clarified in [108]-[111], The influence of HHO gas on the performance and the emission characteristics of a Skoda Felicia 1.3 GLXi engine at different engine speeds was investigated. Result in the efficiency of engine increased to 10% as the use of HHO gas and adding it into the air-fuel mixture, hence decreasing the fuel consumption up to 34%. [112] studied the performance of a single/cylinder spark ignition (SI) engine operated with hydrogen. It was revealed that the brake thermal efficiency (BTE) when hydrogen was used increase with the increase of the engine speed, reaches its maximum of 25.99% at 1700 rpm and then reduce the rising of engine speed. [113] added a hydrogen injection system and a hybrid electronic control unit to a gasoline engine to transform it into a hybrid hydrogen/gasoline engine (HHGE), and tested it in cold start, idle, and partial load scenarios. The test findings showed that adding hydrogen improved thermal efficiency, particularly in lean and idle situations. [114] The maximum brake torque and the thermal efficiency determined as a function of the engine speed and throttle opening for the Volkswagen Polo 1.4 A04 engine running on hydrogen/gasoline bi-fuel at $\lambda$=1.6 were investigated. A maximum torque of approximately 65 N.m was achieved at 4000 rpm and a full load. This value is less than the obtained value at 3800 rpm under full/load gasoline operation. Otherwise, a relatively peak thermal efficiency about 35% is achieved, which is better than the typical obtained values of gasoline fuel engines. [115] A single/cylinder SI engine operating with different hydrogen gasoline blends at high speed was studied. The results showed that the peak value of Bmep was determined at the speed of 3000 rpm shown in Fig. 20, and the brake thermal efficiencies of the hydrogen/enriched operation were greater than those of gasoline fuelled engine at all speeds of the engine.

### 8.2. Engine Torque

Engine torque is developed on the crankshaft as the piston pushed by the cylinder pressure in the power stroke and is used to predict the engine power that is produced, and the measurand is a torquemeter. The engine torque or moment of the turning depend on the horsepower and is transferred through the reduction gear propeller. [116] experimentally investigated a hydrogen/enriched gasoline engine at different operating conditions. It was indicated that to make the addition of hydrogen more effective, it is added at lowering cyclic variation of the engine at small loads than at large loads. [117] The performances of an SI engine fueled with the hydrogen that is extracted from industrial byproducts and gasoline were studied. As the load grows, the brake specific gas-fuel consumption reduces (Fig. 21), and the BTE grows by 15.39% and 11.58% at operating loads of 2.5 bar and 5 bar, respectively. [118] A spark/ignition engine fuelled by hydrogen and gasoline gas was investigated under various engine load operating conditions (25%, 50%, 75%, and 100%) and different hydrogen gas mass fractions operating condition (3%, 6%, and 9%). An increase in the load led to decrease the BSFC of the engine at various hydrogen concentrations (Fig. 22). [119] The combustion and performance of direct-injection SI engines at medium to high loads with different ignition systems were studied. The indicated thermal efficiency of all ignition systems first increased and then decreased with increasing load (Fig. 23). [120] The hydrogen addition effect on the performance and emission characteristics of a spark/ignited (SI) gasoline engine at different loads and lean operating conditions was studied. The mean effective pressure (Bmep) of the engine brake raised just at low/load conditions after the addition of hydrogen. but the hybrid hydrogen-gasoline engine (HHGE) developed a lower Bmep than did the original engine at high loads of the engine. [121] Investigated a spark/ignition engine as the addition of hydrogen and methanol. The experiments focused on the performance with the use of pure gasoline, methanol/gasoline, and hydrogen/methanol/gasoline fuel combinations at different loads of the engine (25 Nm, 50 Nm, 75 Nm, and 100 Nm, 100%), various lambda values (0.8, 1, and 1.2), and a constant speed of the engine (2000 rpm). The BTE of the engine raised as the engine load enlarged for all used fuels (Fig. 24).

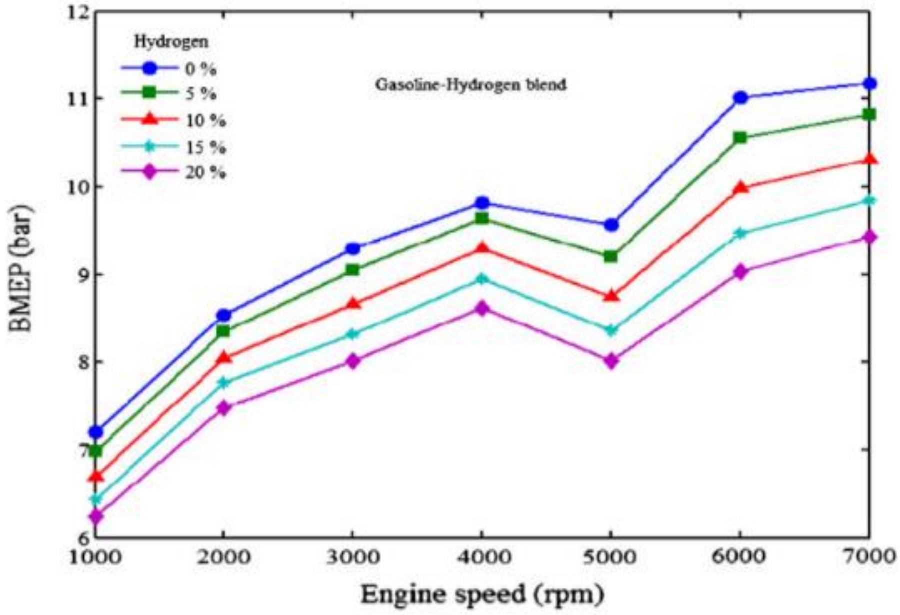


**Fig. 17.** BMEP versus engine speed in case of adding hydrogen, [106]

## 8.3. Injection and Ignition Timing

The ignition timing, fuel injection timing and injection duration are important engine control parameters used to get an efficient range of fuel consumption, power output and developed performance. [122] The delay in the timing of injection and ignition in an engine powered by hydrogen, the indicated power and indicated thermal efficiency at the beginning rise and then reduce. [123] When the optimal injection timing was reached, adjusting the injection end timing to 80 CA BTDC resulted in an about 1.5% rise in the brake thermal efficiency in comparison with the other injection strategies (Fig. 25). [124] investigated the characteristics of engine performance at various fuel injection timings. The 350 crank angle degrees (CAD) fell near the top dead center (TDC) when the fuel injection time dropped from before the top dead center (BTDC), according to the data. Efficiency and the extra air ratio increased, and the smallest rise in the peak torque ignition timing evolved (Fig. 26). [125] The results obtained indicated that the performance characteristics of engines running on hydrogen are significantly impacted by the spark timing (ST); when the ST is delayed, the BMEP and BTE first increase and thereafter decrease. [126] The combustion of artificially made producer gas (PG) and hydrogen mixtures in an optical SI engine at a constant speed and stoichiometric ratio but with various spark timings was investigated. The spark timing increased as H2 was added to the PG. [127] examined how well a modified gasoline direct injection engine running on hydrogen and gasoline biofuels performed at various second timings for the fuel injection. It was shown that 130 CAD ahead of the top dead center is the ideal time for the second gasoline direct injection to achieve maximum performance. [128] A four-cylinder, port-injection gasoline engine that was converted to an electronically controlled hybrid hydrogen/gasoline engine (HHGE) was used to study the effects of different spark timing on a hydrogen/gasoline fuelled engine, with a focus on the performance parameters at lean operating conditions. Hydrogen was added to the intake manifolds through a port-injection system while maintaining the original gasoline injection system. It was shown that when the spark strength increased, the thermal efficiency first increased and subsequently decreased. [129] examined the use of gasoline and hydrogen fuel in a single-cylinder, four-stroke engine at varied ignition timings and hydrogen percentages. It was observed that the fuel consumption decreased and the thermal engine efficiency increased when the ignition timing approached top dead center (TDC) at 30 BTDC.

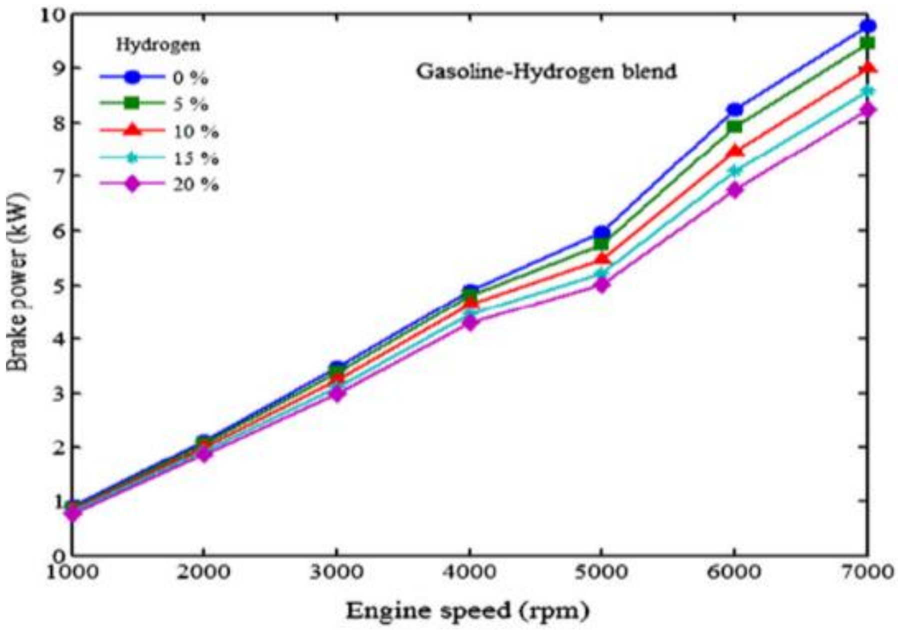


**Fig. 18.** Variation of BP with speed, [106]

### 8.4. Hydrogen Fraction in the Mixture

We can decrease the use of gasoline by raising the hydrogen concentration in a hydrogen/gasoline biofuel engine. [130] Hydrogen blending with gasoline can increase the ITE (indicated thermal efficiency) by 6.5%. [131] The addition of hydrogen increases the brake thermal efficiency for a given equivalence ratio. [132] proved that a gasoline DI engine's BP and BT may be developed under common standard settings, such as 1500 rpm and 2000 rpm, by adding less than 3% hydrogen to the engine. [133] The brake power and brake thermal efficiency were increased by the mixing of hydrogen and gasoline. [134] The use of hydrogen in addition to (acetone-butanol-ethanol) improve the combustion process, especially at lean/burn operating conditions. [135] The mixing of hydrogen and methane at hydrogen concentrating between 0.4 and 0.6 $H_2$ at air/fuel ratio close to stoichiometric and a speed of engine between 2000 and 3000 rpm can enhance the engine performance. [136] The spark ignition engine parameter were investigated using hydrogen which contain $H_2/O_2$ gas when the engine is running at small power and various H2/O2 gas ratios which range from 0 to 7.9% of the gasoline mass.

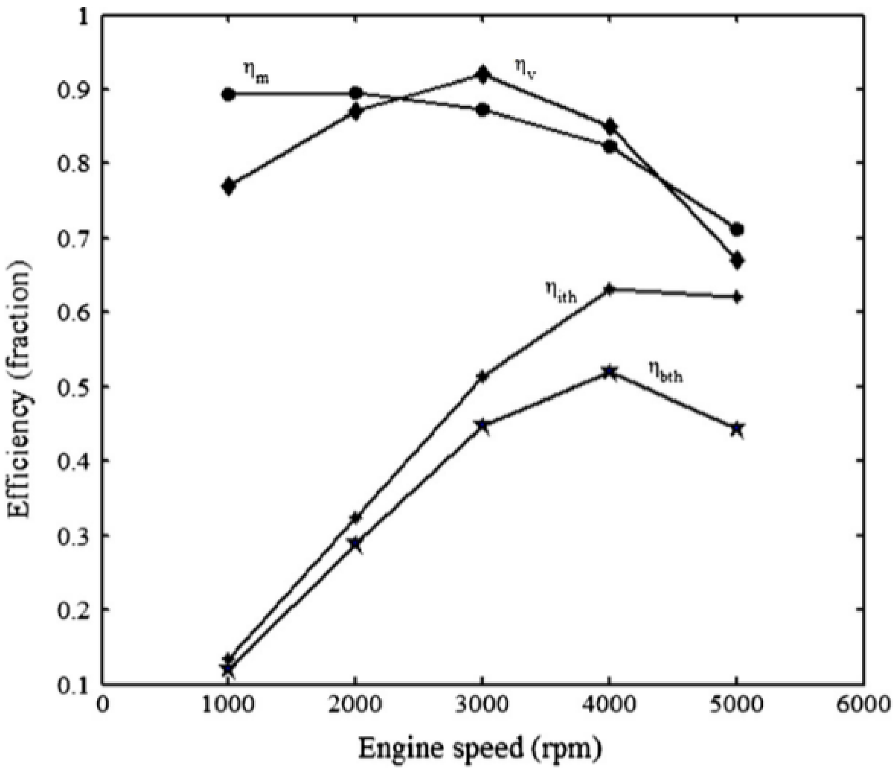


**Fig. 19.** Variation of the mechanical efficiency indicated thermal efficiency, volumetric efficiency, and brake thermal efficiency, [106]

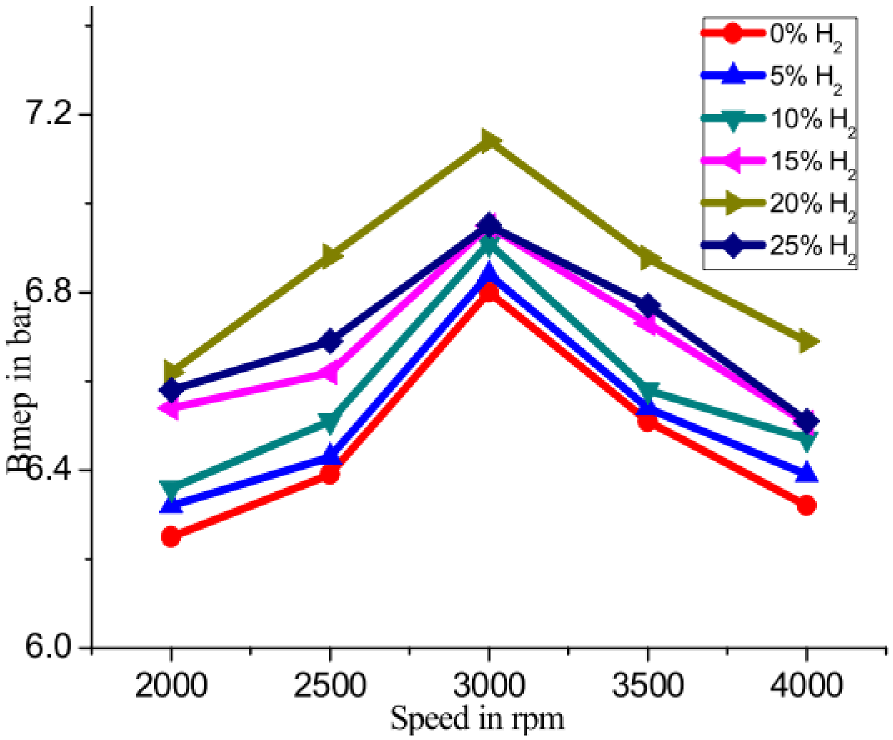


**Fig. 20.** Bmep versos speed in case of different hydrogen volume ratios, [116]

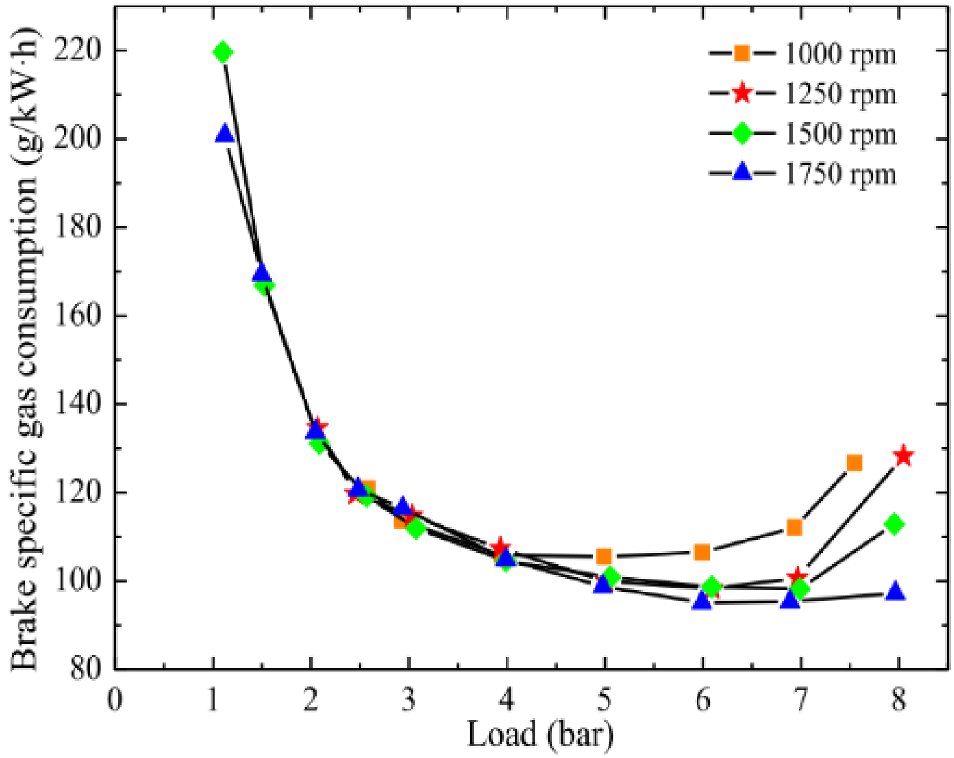


**Fig. 21.** BSGC of the SI engine under various speeds and loads, [118]

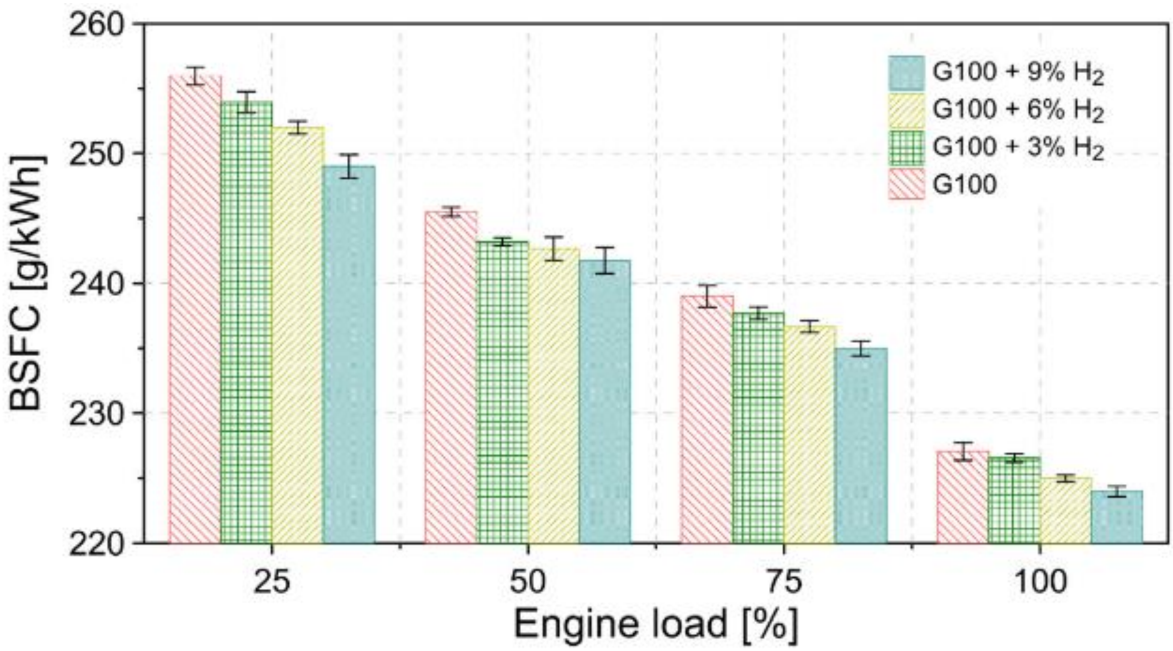


**Fig. 22.** Brake specific fuel consumption of the engine for different load conditions, [119]

The more addition of $H_2/O_2$ gas can reflected in a rise in the indicated power and the indicated efficiency and a reduce in brake/specific fuel consumption. [137] The effects of hydrogen direct injection strategies on hydrogen–gasoline engines at a constant engine speed were studied. The test results showed that a 10% hydrogen fraction increased the mean effective pressure and brake thermal efficiency. [138] The H2O2/ethanol mix direct injection (DI) and gasoline port injection at a multi-injection engine were investigated at various $H_2$ $O_2$ fraction of 0%, 5%, 10%, 15% and 20%. The peak IMEP was determined at $H_2$ $O_2$ = 15%, which was 0.09–0.11 bar higher than that at

$H_2O_2$ = 0%, and the maximum BTE was 0.86%, 0.75%, 0.71% and 0.75% higher than that at $H_2O_2$ = 0%, respectively (Fig. 27). [139] The addition of a gaseous hydrogen mixture (HGM) to primary fuel in a single/cylinder research engine (SCRE) were evaluated. It was indicated that the use of reformed gas decreases the specific fuel consumption. [140] The performance of the investigated hydrogen/gasoline dual/fuel engine at various hydrogen flow rates was investigated.

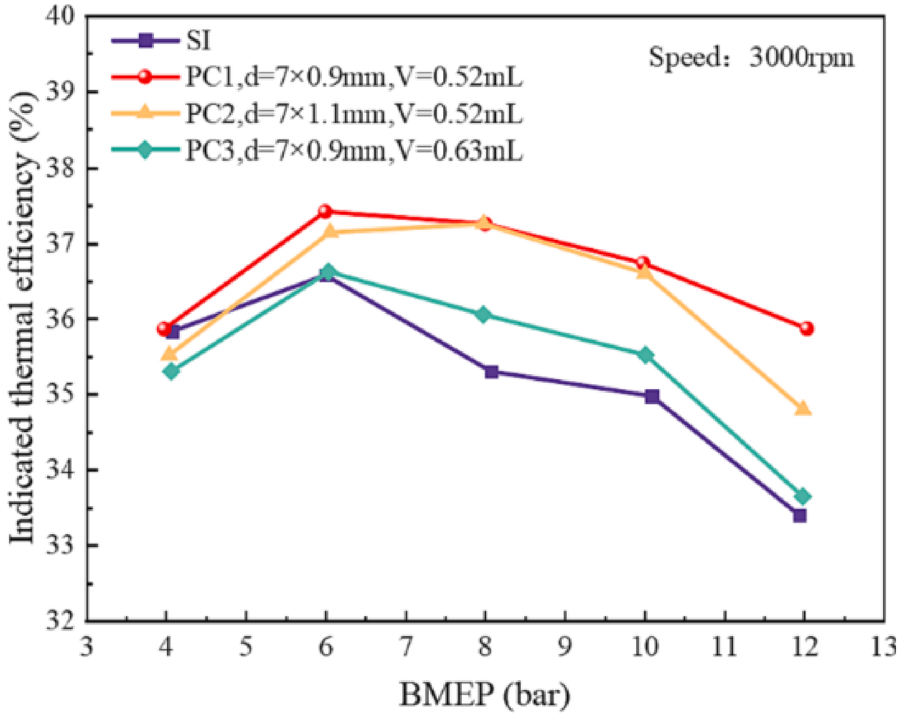


**Fig. 23.** Trends of indicated thermal efficiency with load for different ignition system, [120]

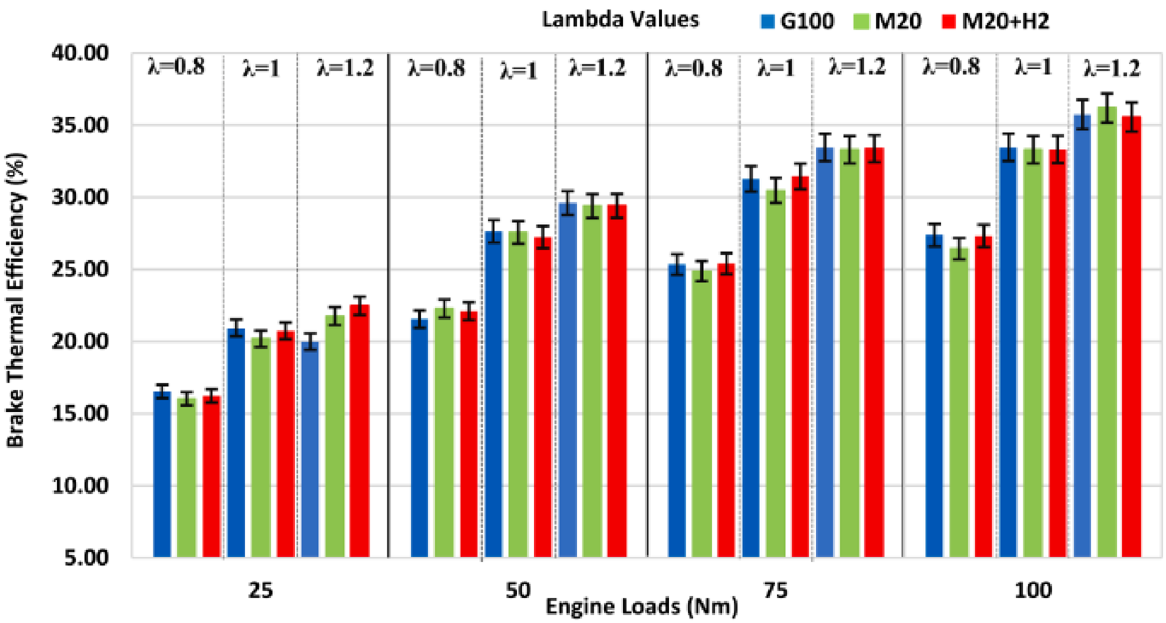


**Fig. 24.** The thermal efficiency of test fuels at various lambda values and engine loads, [122]

The pressure, exhaust gas temperature, brake mean effective pressure, and brake thermal efficiency all increase with the usage of hydrogen in the cylinder. [141] The study focused on a four-stroke, single-cylinder spark ignition engine that ran on gasoline at various hydrogen volume ratios: 24%, 26%, 27%, 28%, 29%, 31%, 35%, 37%, and 49% of the total intake volume, Fig. 28

illustrates how the engine's performance improved in terms of thermal efficiency and reduced the amount of fuel used for the brakes and specific purposes. [142] Under various hydrogen content (2, 5, 8, 11, and 14 LPM), an attempt was made to ascertain the impact of hydrogen addition on the performance of an SI engine with hydrogen port induction and gasoline DI. Brake thermal efficiency rose by 25% at the given hydrogen content.

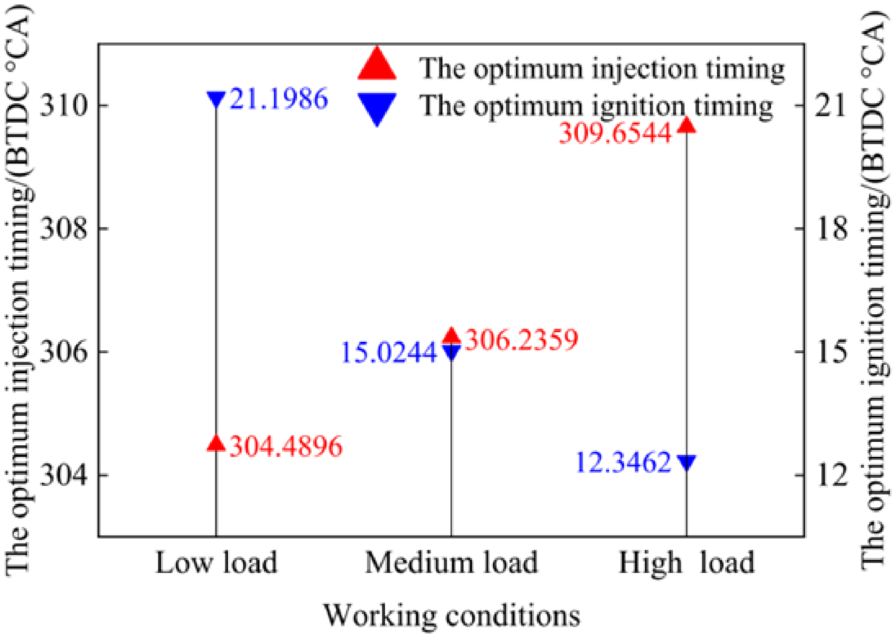


**Fig. 25.** Injection timing of hydrogen for different conditions, [124]

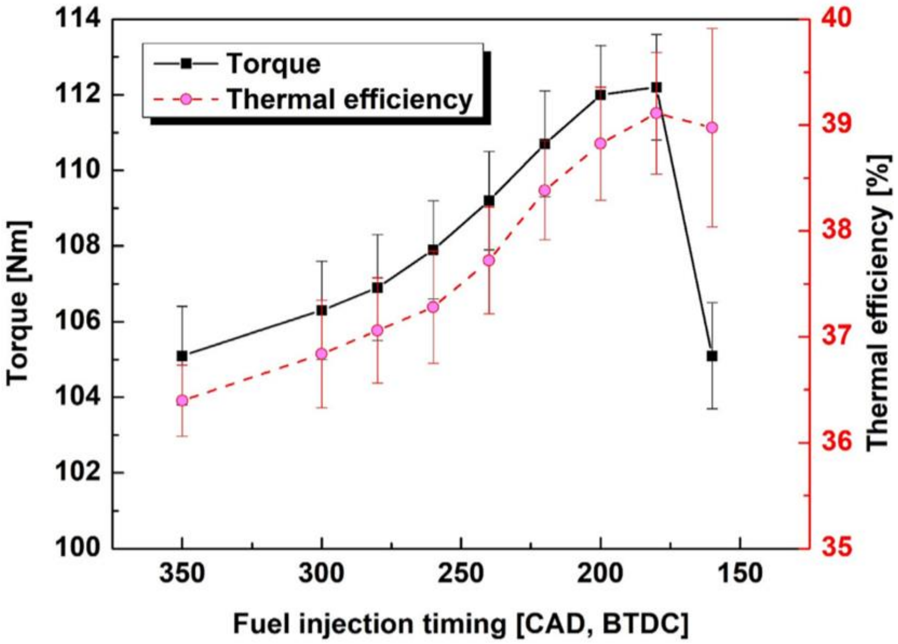


**Fig. 26.** Variation of Torque and thermal efficiency, for various fuel injection timings, [125]

### 8.5. Excess Air Ratio

The excess air ratio, which is dependent on engine parameters, fuel type, and standard circumstances, is a useful indicator of a SI engine's performance. [143] When combustion was first starting at slower speeds, the impact of the air/fuel ratio was more noticeable than when it was burning quickly at faster rates. [144] studied a dual/fuel SI engine with gasoline port injection and hydrogen direct injection (HDI) at small speed and low load under five different excess air ratios. It was demonstrated that while the engine's surplus air ratio increased, the brake thermal efficiency first increased, then decreased, and finally peaked at an engine's excess air ratio of 1.1 (Fig. 29). [145] At low engine speeds and light loads, the brake thermal efficiency (BTE) of a hydrogen-fueled engine increases as the surplus air ratio rises. [146] Suggested that raising lambda and the hydrogen mass percentage would improve the maximum thermal efficiency (Fig. 30). [147] The investigation was conducted at different hydrogen addition levels and excess air ratios in order to better understand the potential of ethanol as a clean engine fuel when paired with lean operation conditions.

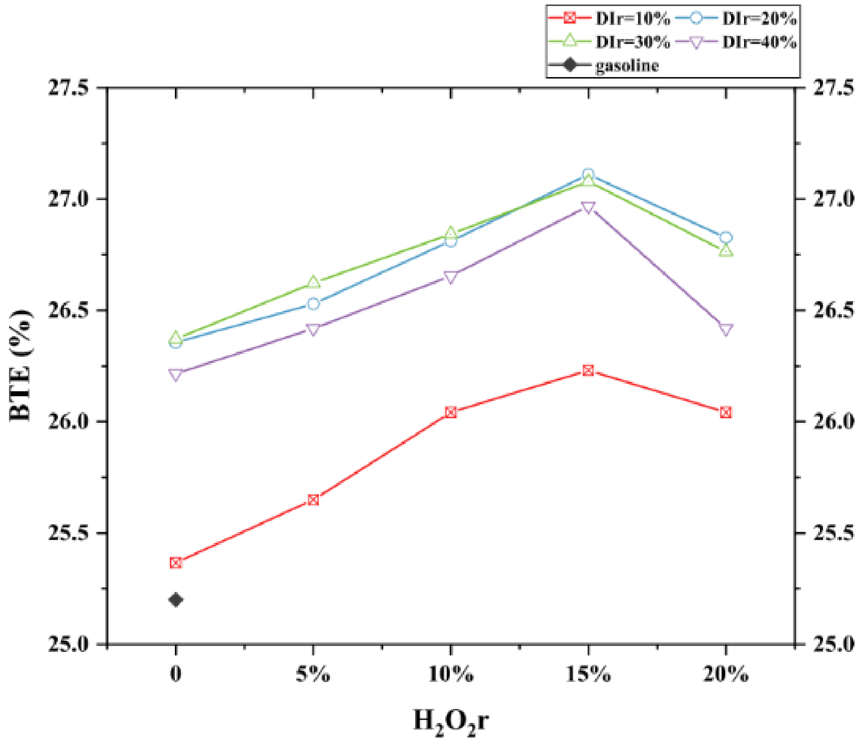


**Fig. 27.** BTE with $H_2$ $O_2$ addition, [139]

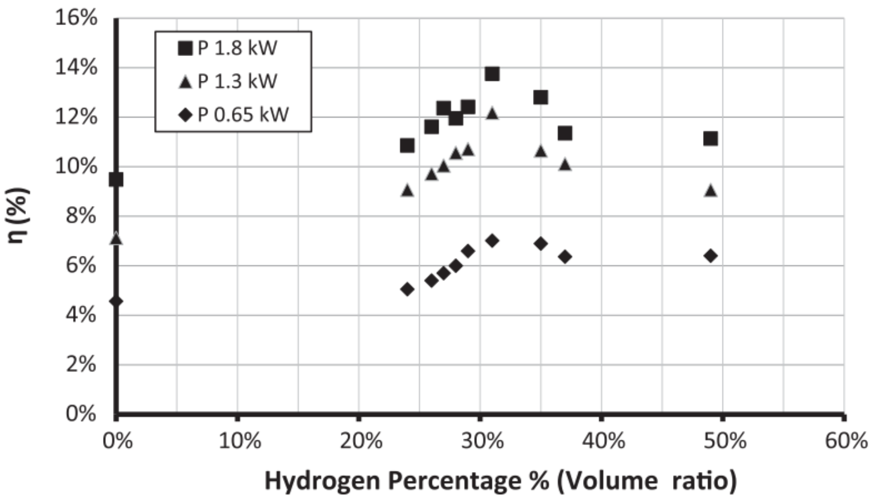


**Fig. 28.** Break thermal efficiency at different power, [142]

The findings demonstrated that, up to a 20% air excess, the addition of hydrogen fuel had no discernible impact on braking power or the effectiveness of fuel conversion under lean operating conditions. In the event of a 40% surplus air operating situation, however, it is necessary to inject

6% $H_2$ in order to achieve the desired power output while simultaneously improving fuel conversion efficiency. [148] Investigated the combustion of a hybrid hydrogen/gasoline engine (HHGE) at idle and lean running circumstances with different surplus air ratios by conducting an experiment on a four-cylinder SI gasoline engine that was run with a hydrogen port/injection system The results revealed that the addition of a 3% hydrogen fraction increased the reported thermal efficiency at an excess air ratio of 1.37 from 13.81% for the regular gasoline engine to 20.20% for the HHGE. [149] The mixture of hydrogen and gasoline improved the brake thermal efficiency and maintained it roughly constant throughout a range of excess air ratios.

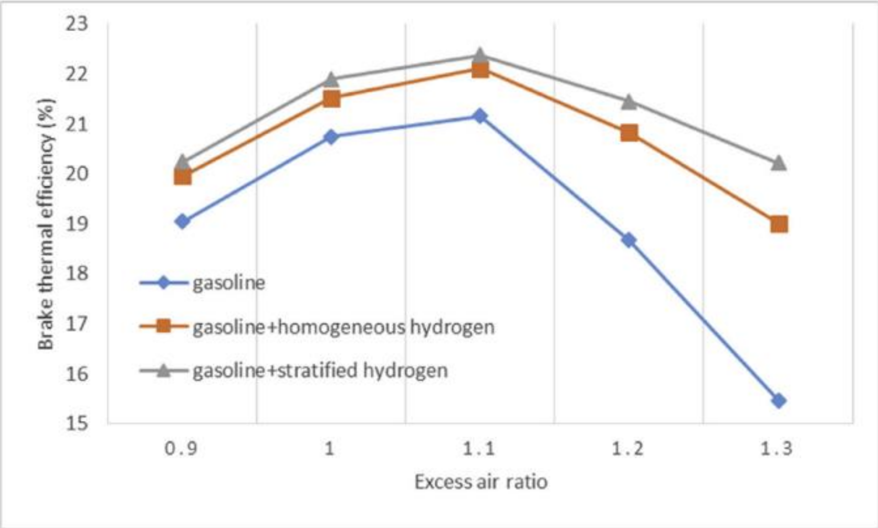


**Fig. 29.** Excess air ratio with brake thermal efficiency, [144]

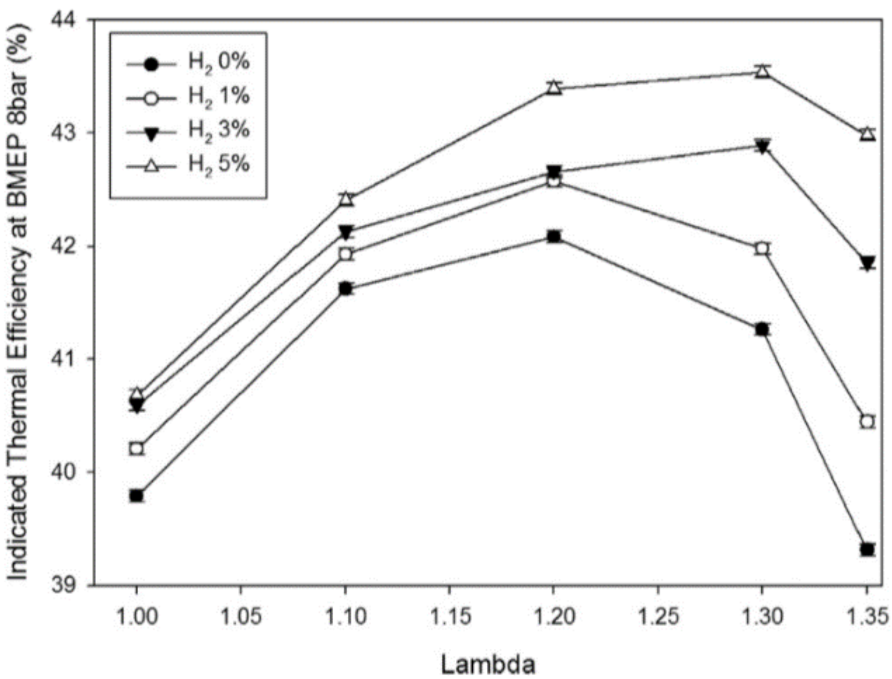


**Fig. 30.** Indicated thermal efficiency on BMEP 8 bar at lambda, [147]

## 9. Engine Performance for Ethanol/Gasoline

One of the most used renewable fuels and the best of them is ethanol which has a notable effect on the performance of SI engine. Gasoline is widely used and mixed with another alternative fuel and used in the last century with the improvement of spark ignition engines and the automotive industry. Ethanol is mixed with gasoline and improve the performance of engines due to hydrogen bonding, and the mixing of ethanol and gasoline can be done at various ethanol ratios. Each mixing ratio shows different characteristics. Many studies on the use of ethanol/gasoline fuels in SI engines to enhance performance have been done.

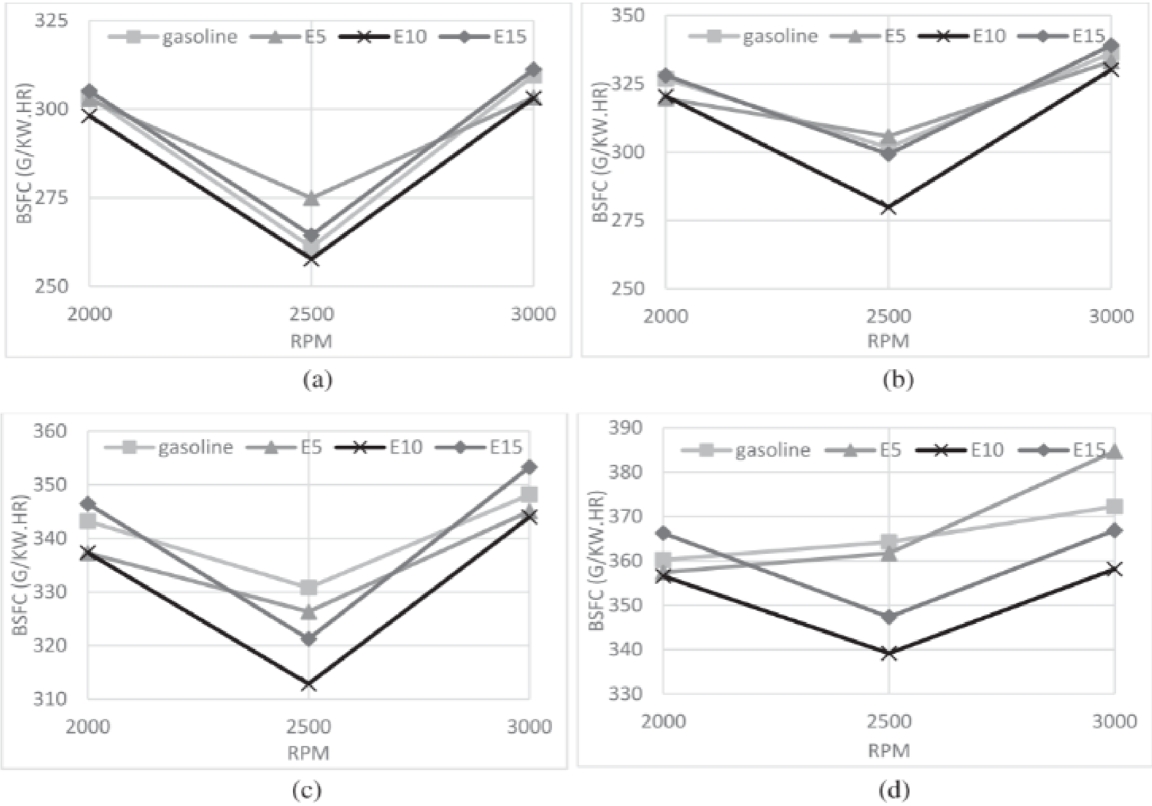


**Fig. 31.** B. S. F. C with engine speed (a) 25% load, (b) 50% load, (c) 75% load, (d) full load, [153]

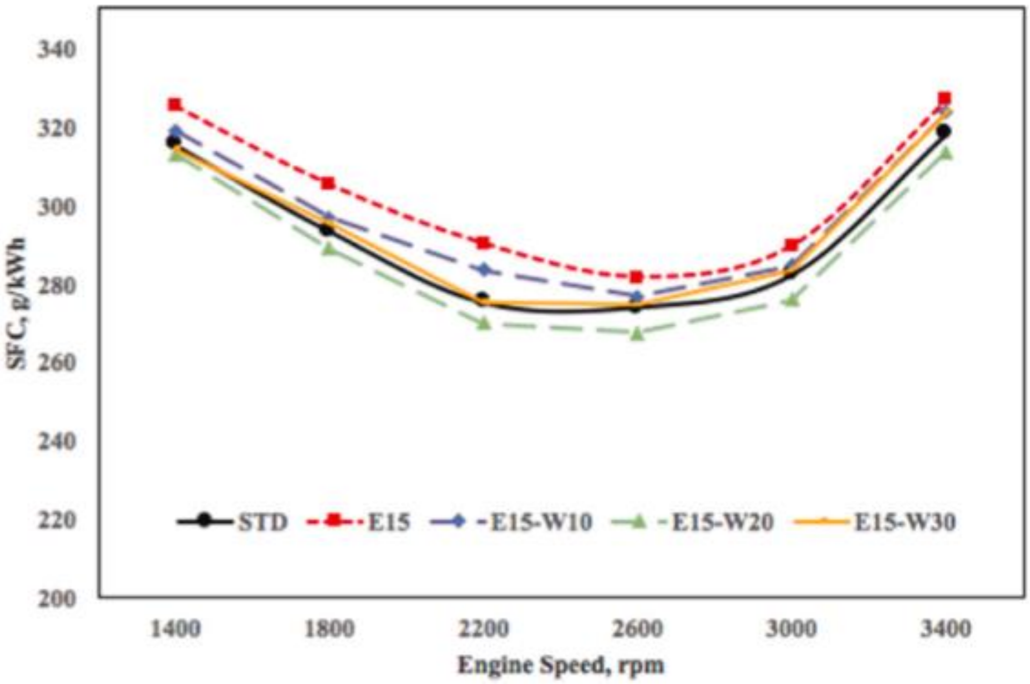


**Fig. 32.** Fuel consumption with speed, [154]

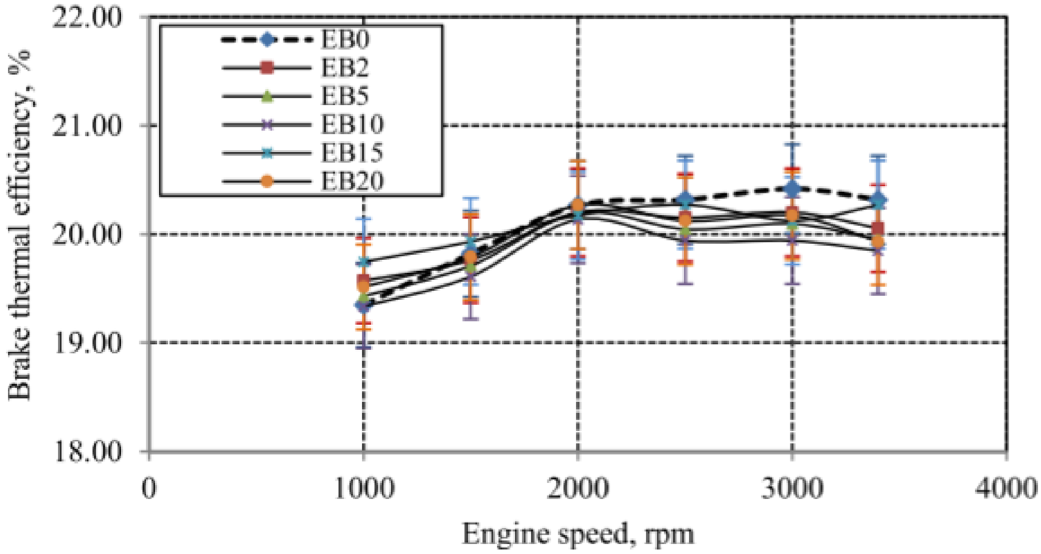


**Fig. 33.** Brake thermal efficiency for different fuel types, [157]

### 9.1. Engine Speed

Speed has a significant effect on ethanol-gasoline engines. [150] showed that BTE is lower at lower engine speeds and subsequently increases with engine speed, and BSFC decreases with increasing engine speed. An increase in speed improves performance indicators like BMEP, BT, BTE and BSFC for spark/ignition (SI) engines using ethanol-premium gasoline bifuel [151]. [152] Investigated different mixing ratio of ethanol/gasoline blends at various engine speeds and loads. The specific fuel consumption was at its minimum value at 2500 rpm, except for in the 100% load study (Fig. 31). [153] studied various ratios (10%, 20% and 30%) of the water that has been injected at the intake port of the manifold of an engine fuelled by ethanol/gasoline blend. This study has been done at the maximum open position and at different engine speeds of 1400, 1800, 2200, 2600, 3000 and 3400 rpm. It was indicated that the specific fuel consumption was at minimum value when the engine operated at 2600 rpm and a 20% water injection rate, according to the STD situation (Fig. 32). [154] The performance characteristics of SI engine operated with ethanol/gasoline blends along with hydrogen injection are investigated at different speeds, such as 1800, 1600, 1400, and 1200 rpm. At 1200, 1400, 1600, and 1800 rpm, the pressure increase in E30 was 70%, 66%, 22%, and 72% less than that of gasoline, respectively. [155] An increase in engine torque up to an engine speed of 2200 rpm was observed with increasing speed. At engine speeds above this speed, there was a reduction in the engine torque. [156] The effect of various ethanol-gasoline/butanol fuel mixtures on the performance of a gasoline engine was studied. It was focused on investigate the engine performance parameters, like the engine brake power, BTE, and BSFC, under various operating conditions of engine speed and engine load. The maximum BTE of 20.32% was obtained when the engine was runed at 3000 rpm (Fig. 33). [157] investigated ethanol-gasoline blends in a SI engine. It was indicated that the blended fuels produced were very similar to the engine characteristics of pure gasoline. [158] The torque with mixed fuels (E50 and E85) was generally greater than that with base gasoline (E0) in all speed ranges.

### 9.2. Engine Torque

An increase in the load leads to an increase in the brake thermal efficiency of an engine fuelled by an ethanol/gasoline mixture, as shown in Fig. 34, and a reduction in the brake/specific fuel consumption [159]. [160] showed that the peak cylinder pressure rise, and the corresponding cycle-by-cycle variations reduce with increasing load. [161] investigated the performance parameters of an engine operated with blend of gasoline-ethanol fuel under various compression ratios and loads. It was showed that the break thermal efficiency raised when an ethanol gasoline blend was used in comparison with gasoline, and the peak BTE was 16% for a low load and 12% for a high load.

[162] Experimentally investigated the use of thermal surface cover for gasoline blends containing ethanol, butanol, and propanol by 100-µm piston surface coatings of magnesium partially stabilized zirconium (Mg-PSZ). The fuel mixture consisted of 20% ethanol and 80% gasoline, 20% butane and 80% gasoline, and 20% propane and 80% gasoline. This study was performed at different loads. It was found that the Mg-PSZ piston coating displays optimal engine performance when used with E20, B20, and P20 gasoline blends. A 1.7% reduction in fuel consumption was observed for Mg-PSZ-coated pistons at E20, while the braking thermal efficiency increased by 4%.

### 9.3. Injection and Ignition Timing

When the ethanol fraction in the fuel composition is higher than gasoline, the ignition timing at which the torque at the peak value is less than the ignition timing when the ethanol fraction is more than gasoline [163]. [164] investigated the effects of ethanol fuelled engine injection timing (430 °CA, 570 °CA, 620 °CA and 670 °CA) and injection pressure (40 bar, 60 bar and 90 bar) at the performance and emission of SI engine fuelled by ethanol direct injection (EDI) and gasoline port injection (GPI) engines. When the ethanol injection time was 430 °CA (EDI430), the IMEP enhanced at different injection pressures (Fig. 35). [165] studied the different fraction of acetone/butanol/ethanol (ABE) and gasoline blends effect on the performance of a four-stroke, high speed spark ignition engine operated with four different types of fuels: pure gasoline and gasoline mixed with 10%, 20% and 30% ABE. Gasoline blending with ABE can increase the spark timing. The spark timing of an engine fuelled by ABE-30 can be advanced by 5.34° CA relative to that of an engine fuelled by pure gasoline. [166] The combustion performance of a single-cylinder SI engine with stoichiometric air/fuel ratios under different injection modes was investigated. The BMEP increased with increasing ethanol ratio under the different injection modes. [167] Examined injection timing using both single and double injection strategies on a turbocharged gasoline direct injection (GDI) engine fuelled with a blend of gasoline and ethanol at a stoichiometric air/fuel ratio. It was found that the peak combustion pressure, maximum heat release rate, and maximum in-cylinder temperature exhibited an initial increase followed by a decrease as injection timing was advanced from 340 °CA bTDC to 280 °CA bTDC, peaking at 300 °CA bTDC.

### 9.4. Ethanol Fraction in the Mixture

Ethanol, which is usually delivered in pure or splash-blended form with gasoline, can increase engine efficiency when utilized in S.I.E. But this isn't the best way to use ethanol because it tends to increase fuel consumption that is unique to the brakes [168]. Because of the latent heat of vaporization and the vaporization properties of ethanol, fuel compositions with larger ethanol fractions are more effective for generating power [169]. According to [170] a little addition of ethanol can boost brake thermal efficiency by around 7% and braking power by 9%. [171] discovered that the use of ethanol/gasoline mixes causes a little rise in fuel consumption and engine torque output. [172] used gasoline and ethanol in a single-cylinder spark ignition (SI) engine at a fixed engine speed and stoichiometric air/fuel ratio, with ethanol ratios varied from 0% to 100%, to study the combustion characteristics of a dual-fuel dual-injection (DFDI) engine. A higher ethanol percentage typically results in higher brake mean effective pressure (BMEP) and thermal efficiency. [173] experimented to determine the ideal ethanol-gasoline blend rate for maximizing brake thermal efficiency in a commercial SI engine. They found that brake thermal efficiency peaks when the engine runs at 58–73% of wide-open throttle (WOT) at an engine speed of 2000–2500 rpm, using E40 and E50 fuels. [174] Through the use of CFD modeling, an experimental investigation was conducted into the charge cooling effect and combustion characteristics of ethanol direct injection in a gasoline port injection (EDI + GPI) engine on a single-cylinder spark ignition engine over the full range of ethanol ratios from 0% (GPI only) to 100% (EDI only). The IMEP, thermal efficiency, and emissions of this EDI + GPI engine may be maximized at ethanol ratios ranging from 40–60%, according to the findings of the experimental and computational analyses. [175] used an artificial neural network (ANN) to analyze the performance of a four-stroke SI engine running on ethanol-gasoline mixtures of 0%, 5%, 10%, 15%, and 20%. The engine's reported power and peak torque output were slightly enhanced when ethanol/gasoline mixed fuels were used (Fig. 37). The engine's claimed thermal and volumetric efficiencies were also slightly lowered (Fig. 36).

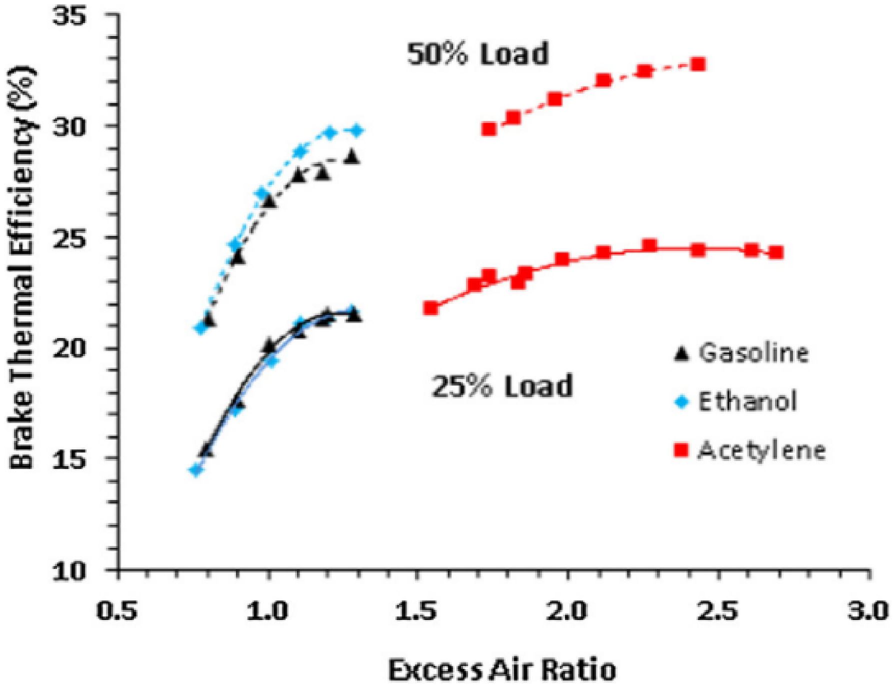


**Fig. 34.** BTE versus EAR at different fuels, [160]

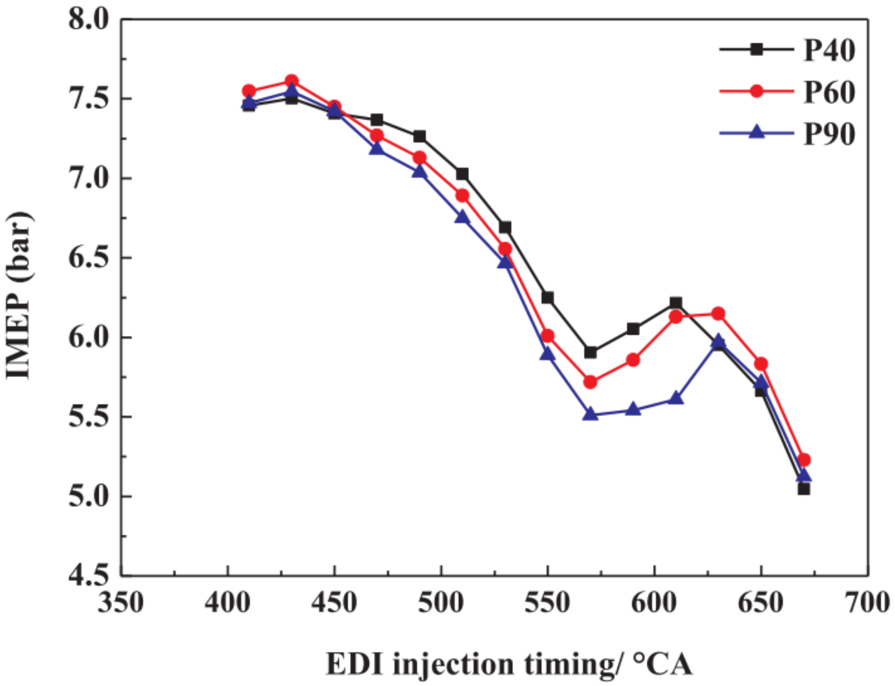


**Fig. 35.** IMEP with injection timing, [165]

### 9.5. Excess Air Ratio

The excess air ratio (λ) is a crucial parameter in engine operation. As the excess air ratio increases, the ignition timing is delayed, the combustion period lengthens, and the heat release rate decreases, while emissions tend to rise [176]. [177] examined the effects of adding ethanol at various excess air ratios on knocking and performance characteristics, including output power and indicated thermal efficiency (ITE), in a single-cylinder, four-stroke SI engine. Compared to pure gasoline, the IMEP and ITE of E100 showed increases ranging from 6.3% to 15.1% and 6.8% to 9.1%, respectively, at different λ values. [178] conducted experimental research on a dual-injection spark ignition (SI) engine, comparing three injection methods: ABE port injection plus gasoline direct injection (A + G), gasoline port injection plus ABE direct injection (G + A), and gasoline port injection plus gasoline direct injection (G + G) under varying λ values, engine speeds, loads, and ignition timings. The G + A mode achieved the highest brake thermal efficiency (BTE), which was 0.2%, 0.4%, 0.02%, 0.05%, and 0.6% greater than that of the G + G mode at λ values ranging from 0.9 to 1.3, respectively. [179] investigated the performance and emissions of a dual-fuel injection engine with ethanol port injection and gasoline direct injection under lean burn conditions. The maximum temperature (Tmax) decreased when gasoline was added at λ = 1 and 1.2 but increased when gasoline was added at λ = 1.4.

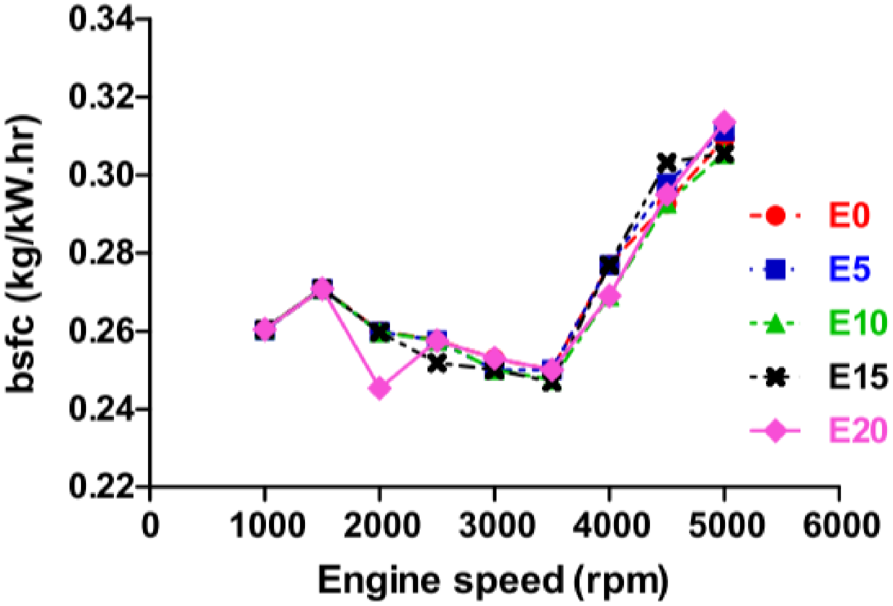


**Fig. 36.** bsfc at different fuel blends and engine speeds, [176]

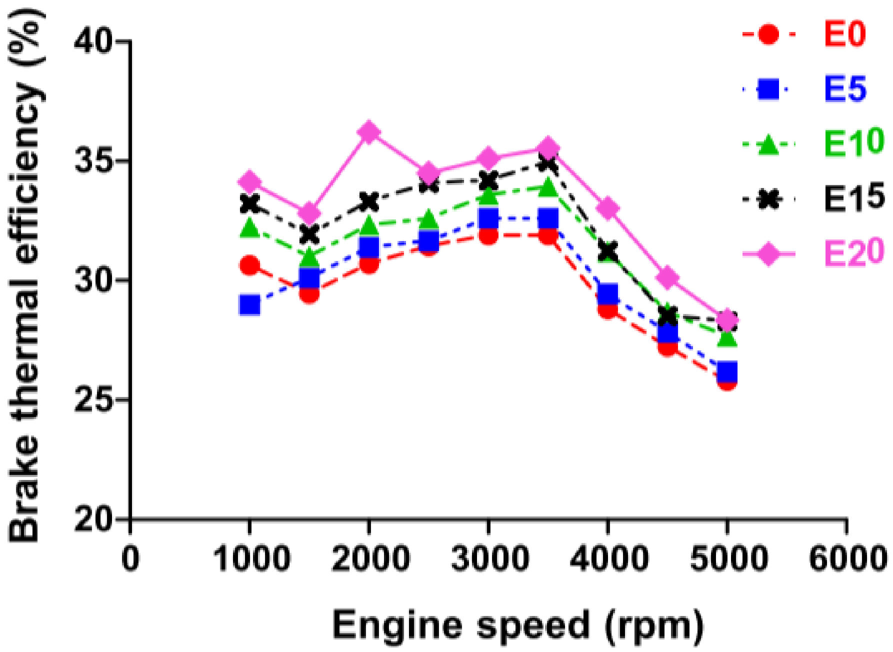


**Fig. 37.** Brake thermal efficiency at different fuel blends and engine speeds, [176]

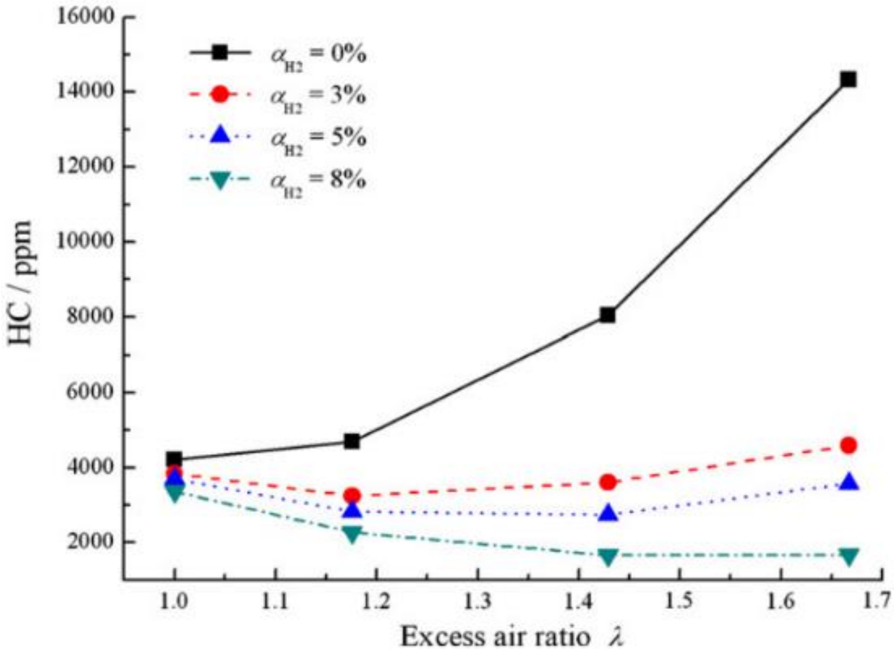


**Fig. 38.** HC with excess air, [189]

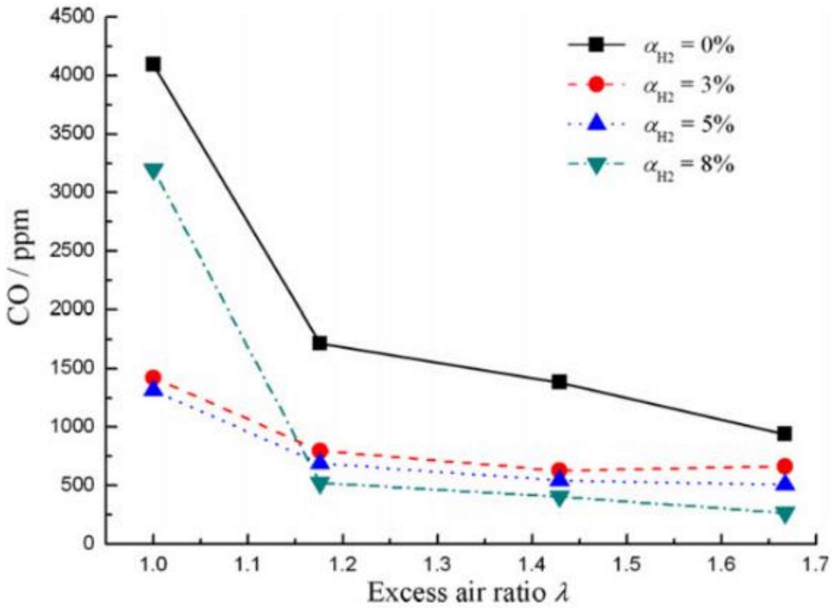


**Fig. 39.** CO against excess air, [189]

## 10. Engine Performance of a Natural Gas

Natural gas (NG) is the most important and widespread alternative fuels for SI engines [180]. Compressed natural gas (CNG) is used as an important alternative fuel in SI engines to enhance the specific fuel consumption and exhaust gas emissions but it reduced the performance characteristics of the engine [181]. Natural gas has a high autoignition temperature which le to make it in need to a high compression ratios and/or intake charge preheating to achieve homogenous charge compression ignition (HCCI) engine operation [182]. [183] Investigated compressed natural gas (CNG)-fuelled SI engines at rich conditions at various compression ratios and different equivalence ratios. It was observed that both brake thermal efficiency and brake power output improve with an increase in the compression ratio, reaching a maximum brake thermal efficiency of 30.2% at a compression ratio of 12.5:1, with further gains observed beyond this critical value. [19] investigated the effects of fuel injection timing on engine performance, combustion, and emissions, finding that these effects were particularly pronounced in the case of delayed injection. [184] examined the impact of the excess air ratio on engine performance and emissions in a spark ignition engine using three different fuels: gasoline, compressed natural gas (CNG), and gasoline–CNG mixture (90% gasoline, 10% CNG: G9C1). The results showed that brake torque for all fuels increased significantly as the blend fraction increased from low to high.

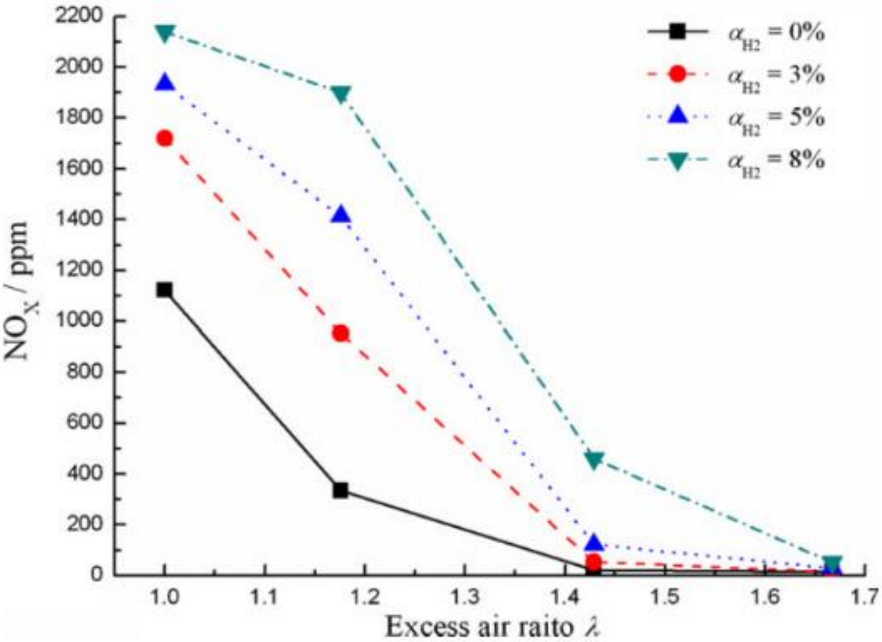


**Fig. 40.** NOx against excess air, [189]

## 11. Engine Emissions

The global demand for energy increase with time, which led to rise the energy costs, and developing environmental concerns reflected in concentrate the research efforts to reduce fuel consumption and the concentration of harmful gases in exhaust emissions. The most serious harmful pollutants in the emissions of SI engines are CO, $CO_2$, $NO_X$, and HC, and the most serious are NO. The formation of NO is highly affected by the in-cylinder temperature, oxygen concentration and residence time for the reaction to occur.

### 11.1. Emissions of Hydrogen/Gasoline Engines

Hydrogen substitution helps to reduce CO2 emissions; despite this advantage, NOx emissions are not reduced [185]. [186] studied the emission characteristics of an SI engine fuelled by gasoline/hydrogen mixed fuel under different hydrogen injection strategies. It was shown that the emissions were slightly greater than those with the premixed hydrogen mixture distribution (PHMD). [187] Investigated the NOx emissions of a turbocharged hydrogen engine at different speeds, loads, equivalence ratios and spark timings. The NOx emission varied from 300 ppm to 1200 ppm as the engine speed raised from 1500 rpm to 2000 rpm, the NOx emission increased, and the maximum value increased as the load increased. The equivalence ratio affected the NOx emission because it influenced the combustion velocity, and the NOx emission decreased as the ST approached the TDC at different loads. [188] studied the emissions of spark-ignited (SI) hydrogen enrichment engines under four different lambda value of 1.00, 1.18, 1.43 and 1.67 and various hydrogen volume fractions at intakes of 3%, 5%, and 8%, respectively. The experimental results showed that HC and CO emissions decreased (Fig. 38 & Fig. 39), but NOx emissions increased with increasing hydrogen addition (Fig. 40). [189] The formation of NO increased with increasing hydrogen addition. [190] The NOx emissions of the supercharger-boosted engine at air excess ratios between 1.4 and 1.8 were lower than those of the turbocharger hydrogen engine, especially at an air excess ratio equal to 1.4, for which the NOx emission of the supercharger-boosted engine was only 170 ppm. [191] studied the effects of H2O2 in spark ignition (SI) engines of an ethanol/gasoline fuelled engine at different excess air ratios ($\lambda$= 0.9, 1, and 1.2). The NOx concentration decreased by an average of 38.0%, 28.8%, and 42.2% at $\lambda$ = 0.9, 1 and 1.2, respectively. [192] studied the effect of hydroxygen (H2 + O2) addition on the emissions of a gasoline engine. Then, water was injected into the intake manifold of the SI engine. The NOx concentration of the test engine increased to 141.1% with the addition of hydroxygen, but it decreased from 141.1% to 82.7% with water injection. [193] Investigated hydrogen directly injected in the aperture edge of a spark plug (SHDI) on a SI turbocharged gasoline/hydrogen mixed fuel under lean/burn conditions at constant speed of 1600 rpm and medium load conditions with different hydrogen volume ratios from 0% to 5.5% and excess air ratios ($\lambda$) up to 1.5. The results showed that, in comparison to those under HPI, the emissions of NOX, HC and CO under SHDI were greater. [194] Studied the combustion and emission characteristics of a gasoline/hydrogen bifuel SI engine with CO2 dilution under various hydrogen volume ratio of 0 and 3%, and the CO2 volume ratio was gradually raised from 0 to 4%. It was found that increasing the CO2 ratio in the intake reduced NOx and increased HC (hydrocarbon) emissions; however, increasing the hydrogen fraction in the intake could effectively decrease HC emissions under CO2 dilution conditions. [195] The combustion and emissions under various hydrogen fraction on a gasoline/hydrogen fuelled engine with exhaust gas recirculation (EGR) were studied. EGR decreased NOx emissions by 54.8% compared with those of the standard gasoline engine. [196] Estimated the fuel injection timing of hydrogen fuel injected on engine emissions by changing the fuel injection timing from before the top dead centre (BTDC) to the 190 crank angle (CAD) toward BTDC 60 CAD. Even if the excess air ratio is low under a relatively high torque load of 155 Nm, the NOx and CO2 emissions exhibit high values of 3000 ppm and 500 ppm or higher, respectively.

### 11.2. Emissions of Ethanol/Gasoline Engines

Ethanol is another fuel derived from alcohol which can be used in spark ignition engines and is also available as a mixture in gasoline in certain ratios; the use of ethanol has been known to lower emission because it increases the oxygen content [197]. The increase in the ratio of ethanol in gasoline/ethanol blends causes the reduction of net power output to be over 23% and NOx-specific emissions to up to 32% [198]. It is stated by [199] that, the levels of HC, NOx and CO2 usually reduce when ethanol and gasoline are blended. More specifically, [200] concluded that as the ethanol content in gasoline rises, the HC and CO emissions are dramatically cut back. In the study [201] engine emissions were analyzed at different values of gasoline/ethanol blend and it was found that with the increase of ethanol content of the fuel mixture, the NO emissions were found to be low while the CO and HC emissions were relatively higher. [202] tried carrying out an assessment of the performance and emissions characteristics of a four-stroke, four-cylinder spark ignition engine, TOYOTA TERCEL-3A operated on a gasoline/ethanol blend. Static analysis of the results showed that fuel with ethanol in it lowered CO and HC emissions but elevated CO2 emissions. [203] examined the SI engine emissions with varying ethanol/gasoline blends and spark timings and injection methods and reported that with increasing ethanol concentration the emissions of CO and No showed a decreasing trend compared to pure gasoline. Last, [204] investigated the emission characteristics of an engine operating with E25, E50, E75, and E100 much the same as. [205] and reported that with E50 fuel, all the specific fuel consumption and all the emissions of CO, CO2, HC and NOx were lower by about 3%, 53%, 10%, 12% and 19%, respectively in comparison to an engine running on pure gasoline.

### 11.3. Emissions of Natural Gas Engines

As the global energy recruitment rises, natural gas (NG) plays an important role in the energy supply. Natural gas is the most cleaner fossil fuel, and it has high energy conversion efficiencies for power generation [206]. [207] The CO, HC, and NOx gas emissions and performance characteristics of a computer-integrated biofuel spark ignition engine retrofitted to use both gasoline and compressed natural gas (CNG). The findings indicated that while CNG reduces CO and HC emissions, it leads to an increase in NOx emissions. [208] investigated the emission characteristics of a port fuel injection spark ignition engine modified to run on compressed natural gas (CNG). An experiment was conducted to compare the operating parameters of the engine when fuelled by gasoline and CNG, both with the same excess air ratio (λ). The results showed that the exhaust emissions of the engine running on CNG increased significantly. Specifically, CO2 emissions decreased by up to 50%, NOx emissions decreased by 20%, and CO and HC emissions decreased by up to 90% and 96%, respectively. [209] studied CNG/E10 biofuel in vehicles and the emission characteristics. It was found that compared with E10, CNG can reduce CO2 emissions by approximately 20%.

## 12. Conclusion

ANNs have now appeared as valuable resources for the study of ICEs and a variety of enhancements in terms of the power-to-weight ratio, as well as the reduction of emissions. The capability to model and estimate the strong functional dependencies between the engine input variables and output parameters is indeed one of the main advantages of using ANNs in the described context, especially because the traditional approaches do not suffice to cover the various aspects of the contemporary engine systems. The use of ANN-based models allows the researchers to design the engines in a much shorter time than the actual experimental testing while at the same time providing more accurate results.

The fact that the change towards lower emissions and new fuels is to be a future trend in the development of motor vehicles, the importance of ANN-based capabilities will likely rise as well. Further studies should focus on improving the ANN models' stability and versatility as to the engine parameters and the fuel properties. Furthermore, the focus could be on the development of the combined modelling approach where ANN is supplemented and integrated with other computational methods to analyze the predictive power of the models under study. However, it is high time to mention that ANNs are one of the present cutting-edge technologies that can help to enhance the question of efficient development of sustainable high-performance ICEs.

To offer practical recommendations convenient for further research in the sphere of ANN utilization for modeling engine performance and reducing emissions, the work is concluded with several specific methodological and strategic directions designed to contribute to the increase of the model stability and compatibility with other methods, as well as the enhancement of the predictive characteristics of the model. These approaches will be helpful to reduce the existing drawbacks of the ANN models which in turn will lead to the improvements and better real implementation of ANN in the realistic engine systems.

1. Improving Model Stability

ANNs are well recognized for their sensitivity to the training data they are fed and their liability to overtraining familiar conditions and thus exhibit high instability in conditions not experienced during the training period. To improve the stability of ANN models, future research should focus on the following specific strategies: To improve the stability of ANN models, future research should focus on the following specific strategies:

- Regularization Techniques: Techniques like L2 regularization or dropout which are types of regularization can also be applied to reduce chances of overfitting as well as increasing the stability of the model. These techniques discourage large weights in the model so that the ANN is forced to learn general trends in data and not the noise bytes or out figures.

Example Strategy: The next research works should investigate the capabilities of dropout layers in the eradication of overfitting problems that are characteristic of ANNs used to model multi-fueled engine systems. One last subset of techniques is based on using bald neurons during recurrent training, which makes the model learn more durable representations, immune to specific training instances.

- Ensemble Learning: Applying methodologies of bagging or boosting may lead to the improvement of the generalization and stabilities of ANN models. These methods are used to combine several models to decrease variance to increase the accuracy. For instance, training several ANN models using different portions of the data and averaging the results that they provide will ensure that the final predictions are more stable.

Example Strategy: Another research area can be regarding the applicability of bootstrap aggregating (bagging) that forecasts the use of the ANN model to predict engine emissions under different operating conditions. This approach minimizes the prediction variance of a model by combining many models and hence increasing reliability in practical applications.

2. Integrating ANN with Other Methods

The results of this study show that despite ANNs being versatile and highly accurate, incorporating them with other modeling techniques can improve their performance and utility. Further work should be directed toward developing integrated schemes with ANN and physics-based models or optimization functions or different machine learning approaches.

Hybrid Modeling: Thus, the next step is to attempt integrating ANNs with physics-based models to translate strengths of data-driven approaches with those of mechanistic models. Herein this approach can assist in handling the difficulties of ANNs in managing situations whereby little information is available while still enjoying the advantages of neural networks in systems.

Example Strategy: A possible application of ANNs was already discussed concerning utilization in a computational fluid dynamics (CFD) model to simulate the combustion of fuels in engines. It implied that the ANN could predict the combustion parameters by the real-time data collected from the sensors as well as the CFD model to give a detailed explanation of the fluid dynamic and thermal behaviors for higher accuracy and better interpretation.

- ANN and Genetic Algorithms (GAs): By integrating ANNs with GAs or PSO, the optimization of engine parameters will be improved. GAs can select and fine-tune the architecture and parameters of the networks and improve the accuracy and performance of the nonlinear systems for ANNs.

Example Strategy: Subsequent studies could utilize the Genetic Algorithm to determine the optimal number of layers across the ANNs used in the prediction of the engine performance as well as the number of neurons across each layer and the learning rates alongside. This approach can be used to automate some extent the process of the model tuning to get more accurate predictions on emissions and fuel consumption.

- Reinforcement Learning (RL): Real-time control of engines through reinforcement learning (RL) combined with ANNs can also be seen as a new outlook towards the deterministic approach. As for RL algorithms, those can learn the parameters of the engine and adapt the necessary changes depending on the feedback of the system and constantly improve when it is used in non-stationary environments.

Example Strategy: A blend of RL-ANN was possible for real-time engine control, according to researchers. The RL agent would just learn how to control the engine system and fine-tune the control factors such as fuel injection, and ignition time to reduce emissions and at the same enhance fuel consumption under different circumstances.

3. Enhancing Predictive Capabilities

As for the limitations in the applications of ANNs for engine performance and emission modeling, future studies should consider the utilization of other architectures and training algorithms to improve the predictive capacity of the models.

- Deep Learning Architectures: As for the shallow ANNs the deep models like CNN and RNN might show better results in the case of high dimensional and sophisticated data of an engine. CNNs are more appropriate to work with spatial data while RNNs are appropriate for model temporal relationships such as the performance of the engine recorded over time.

Example Strategy: Subsequent research could focus on applying the 1D-CNNs approach to the analysis of the time-series data of the engine, like the trends of the temperature and pressure in the combustion chamber in a real-time manner. Availability of causal information and capturing spatiotemporal regularities as well as the characteristic of the system parameters in its dynamic state can enhance the model's forecast precision in the conditions of dynamic amplitudes.

- Transfer Learning: When it comes to working with a new dataset, transfer learning makes it possible to reuse models learned with another dataset while retraining them to a limited extent. This approach is probably most beneficial when data for a certain configuration of engines or a certain kind of fuel is scarce. ANNs trained in large databases from conventional engines can learn new parameters, and predict the efficiency of engines operating in hydrogen or ammonia.

Example Strategy: When it comes to future studies, researchers could use transfer learning to apply an ANN model designed with gasoline engine data and adapt it to work with data coming from hydrogen-fueled engines. It is shown that by adjusting the final parameters of the ANN, the model can learn to predict the performance characteristics of hydrogen engines without requiring retraining for the hydrogen data.

4. Incorporating Real-Time Data and Adaptation

The subsequent works should refine the resilient ANN models fit for time-sensitive information processing and capable of updates according to the changing dynamic engine states such as fuel composition volatility, engine deterioration and atmospherical conditions.

- Online Learning: To make the change happen in real-time, there is a need to include online learning methods that enable the model to update itself depending on the newly received information. This would allow the engine to change its efficiency frequently according to the type of fuel and its quality, environmental conditions and the level of load.

Example Strategy: Academicians could design an online learning system for engine models based on ANN which adjusts the weights and threshold values based on inputs from sensors of the engine and optimizes on the fly the fuel inject settings as well F/A ratios.

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**Abbreviation**

| | | | |
|---|---|---|---|
| ANN | : Artificial Neural Network | HHGE | : Hybrid Hydrogen–Gasoline Engine |
| IC | : Internal Combustion | MBT | : Maximum Brake Torque |
| SI | : Spark Ignition | $\lambda$ | : Excess Air Ratio |
| CI | : Compression Ignition | BSFC | : Brake Specific Fuel Consumption |
| BMEP | : Brake Mean Effective Pressure | BTDC | : Before Top Dead Center |
| IMEP | : Indicated Mean Effective Pressure | TDC | : Top Dead Center |
| BTE | : Brake Thermal Efficiency | CAD | : Crank Angle Degrees |
| ST | : Spark Timing | BP | : Brake Power |
| PG | : Producer Gas | BT | : Brake Torque |
| ITE | : Indicated Thermal Efficiency | ABE | : Acetone-Butanol-Ethanol |
| GDI | : Gasoline Direct Injection | HGM | : Hydrogen Gaseous Mixture |
| HDI | : Hydrogen Direct Injection | SCRE | : Single Cylinder Research Engine |
| EDI | : Ethanol Direct Injection | Mg-PSZ | : Magnesium Partially Stabilized Zirconium |
| DI | : Direct Injection | DFDI | : Dual-Fuel Dual-Injection |

| | | | |
|---|---|---|---|
| $T_{max}$ | : Maximum Temperature | SHDI | : Split Hydrogen Direct Injection |
| NG | : Natural Gas | PPHMD | : Partially Premixed Hydrogen Mixture Distribution |
| CNG | : Compressed Natural Gas | EGR | : Exhaust Gas Recirculation |
| HCCI | : Homogenous Charge Compression Ignition | UHC | : Unburnt Hydrocarbons |
| GIT | : Gas Injection Timings | VOC | : Volatile Organic Compounds |
| EHCC | : Eccentric Hemispherical Combustion Chamber | NOx | : Nitrogen Oxides |
| SHMD | : Stratified Hydrogen Mixture Distribution | CO | : Carbon Monoxide |
| PHMD | : Premixed Hydrogen Mixture Distribution | CO2 | : Carbon Dioxide |
| HC | : Hydrocarbons | LNG | : Liquefied Natural Gas |
| IMEP | : Indicated Mean Effective Pressure | DOE | : Design Of Experiments |
| BMEP | : Brake Mean Effective Pressure | GA | : Genetic Algorithm |
| HCCI | : Homogeneous Charge Compression Ignition | PSO | : Particle Swarm Optimization |
| LPG | : Liquefied Petroleum Gas | RNN | : Recurrent Neural Network |
| NG | : Natural Gas | LSTM | : Long Short-Term Memory |
| TDC | : Top Dead Center | BTDC | : Before Top Dead Center |
| EDI | : Ethanol Direct Injection | RMNM-ANN | : Recurrent Multiplicative Neural Artificial Neural Network |
| GPI | : Gasoline Port Injection | H2 | : Hydrogen |
| DI | : Direct Injection | H2O2 | : Hydrogen Peroxide |
| HHGE | : Hybrid Hydrogen-Gasoline Engine | E0 | : 0% Ethanol, 100% Gasoline |
| E75 | : 75% Ethanol, 25% Gasoline | E25 | : 25% Ethanol, 75% Gasoline |
| E100 | : 100% Ethanol | E50 | : 50% Ethanol, 50% Gasoline |
| ABE | : Acetone-Butanol-Ethanol | HGM | : Hydrogen Gas Mixture |
| WOT | : Wide Open Throttle | PSZ | : Partially Stabilized Zirconium |

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