

Review

# A Critical Review on Artificial Intelligence for Fuel Cell Diagnosis

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**Abstract:** In recent years, fuel cell (FC) technology has seen a promising increase in its proportion in stationary power production. Several pilot projects are in operation across the world, with the number of running hours steadily rising, either as stand-alone units or as part of integrated gas turbine–electric energy plants. FCs are a potential energy source with great efficiency and zero emissions. To ensure the best performance, they normally function within a confined temperature and humidity range; nevertheless, this makes the system difficult to regulate, resulting in defects and hastened deterioration. For diagnosis, there are two primary approaches: restricted input information, which gives an unobtrusive, rapid yet restricted examination, and advanced characterization, which provides a more accurate diagnosis but frequently necessitates invasive or delayed tests. Artificial Intelligence (AI) algorithms have shown considerable promise in providing accurate diagnoses with quick data collecting. This work focuses on software models that allow the user to evaluate many different possibilities in the shortest amount of time and is a vital method for proper and dynamic analysis of such entities. The artificial neural network, genetic algorithm, particle swarm optimization, random forest, support vector machine, and extreme learning machine are common AI approaches discussed in this review. This article examines the modern practice and provides recommendations for future machine learning methodologies in fuel cell diagnostic applications. In this study, these six AI tools are specifically explained with results for a better understanding of the fuel cell diagnosis. The conclusion suggests that these approaches are not only a popular and beneficial tool for simulating the nature of an FC system, but they are also appropriate for optimizing the operational parameters necessary for an ideal FC device. Finally, observations and ideas for future research, enhancements, and investigations are offered.

**Keywords:** fuel cells; artificial intelligence; artificial neural network; genetic algorithm; particle swarm optimization; support vector machine; random forest



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## 1. Introduction

### 1.1. Fuel Cells (FCs)

Currently, the world economy is integrally connected to sustainable electrical energy generation, management, and supply. Traditional energy production methods have already significantly impacted the global environment and climate change. According to newly released research by the International Energy Agency, “Energy-related greenhouse gas

(GHG) emissions would lead to considerable climate degradation with an average 6 °C global warming" [1]. In this scenario, clean energy is a feasible option for making the world a safer and more energy-efficient place to live. Clean energy can be a better solution due to its environmentally benign nature because CO<sub>2</sub> emissions are maintained to a minimum, which is the most basic indicator of the greenhouse effect that causes environmental damage [2].

Energy supplies that are safe, eco-friendly, and dependable are critical for humanity's long-term survival and good quality of life, despite their provision facing economic, social, ecological, and economic problems. It is universally recognized that no solitary energy source can monopolize and regulate the world energy market, and consequently, an energy-mix model, which takes advantage of the availability of usable resources in each country/region or the option of supplying energy resources, has received widespread acceptance. To deal with economic expansion and rising urbanization, conventional fossil fuels such as natural gas, coal, and oil have been the world's primary energy sources [3]. Because of the inadequacy and severe pollution associated with the present power production technology, greener and more productive energy conversion devices that use fossil fuels explicitly have become critical for future energy sustainability and environmental concerns. Fuel Cells (FCs) are a sustainable energy source with the potential to be among the most beneficial and innovative technologies [4]. The usage of FCs eliminates toxic emissions generated by other devices because water is the sole by-product [5]. They are financially free of country politics since they do not entail the usage of long-established fuels such as oil and gas. When using renewable clean resources, FCs are appropriate, have a large capacity, and are long-lasting, resulting in almost zero carbon emissions [6]. According to US Department of Energy data, the FC market grew from \$630 million in 2013 to \$2.54 billion in 2018, demonstrating the rising interest and potential of FCs [7].

FC is an electrochemical device that could transform chemical energy into electrical energy in one route, providing several advantages [8]. As a result of the static nature of FC, there is no noise or vibration throughout the conversion process. As long as both the fuel and the oxidant are accessible, an FC is an energy conversion device that constantly transforms chemical energy in fuel into electrical energy. It outperforms standard combustion-based methods used in vital industries including home electricity, electronics, passenger vehicles, power plants, and military applications. With a 60% or greater electrical energy conversion efficiency and fewer emissions, FCs are more efficient than combustion engines. In terms of renewable energy, the FC is a viable solution. Since the early 1800s, FCs have been researched and developed. FCs are divided into two types based on the electrolyte employed, such as alkaline and acidic FCs, and the working temperature, i.e., low- and high-temperature FCs [9,10]. Every kind has unique characteristics that are required for its usage. Alkaline FC (AFC) [11], Proton exchange membrane FC (PEMFC) [12], direct methanol [13] FC (DMFC) [13], phosphoric acid FC (PAFC) [14], melting carbonate FC (MCFC) [15], and solid oxide FC (SOFC) [16] are devices that use electrochemical processes to turn the chemical energy of the fuel directly into electrical energy using fuels—viz. natural gas, hydrogen, methanol, etc.—and oxidants such as O<sub>2</sub>, air, H<sub>2</sub>O<sub>2</sub>, etc.

Depending on the desired power output scale, FCs can be employed in various applications such as electronics, residential, automobiles, heavy vehicles, commercial buildings, and marine and power operations, as depicted in Figure 1. In general, an FC consists of three fundamental functioning parts. The fuel (e.g., hydrogen, ethanol, methanol, methane) is oxidized at an electropositive anode, i.e., a fuel electrode, an electronegative cathode that undergoes a reduction reaction (to O<sub>2</sub>, air, and other substances). The current is transferred between the two electrodes by ions in an electrolyte put between them.

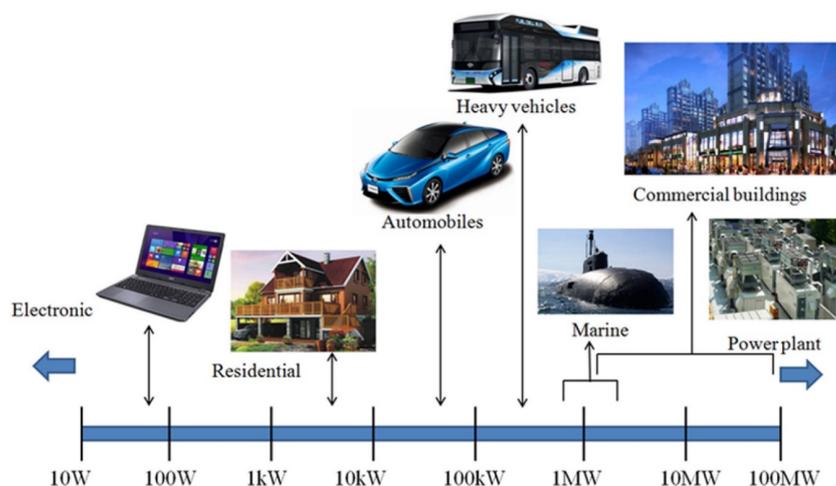


Figure 1. FCs based on a power output scale [17].

On the anode of the FC, the hydrogen is ionized into electrons and protons as shown in Figure 2. The electrons then travel to the cathode, where oxygen is reduced. The protons permeate the electrolyte to join the oxygen species on the cathode, resulting in just water as an end product [18]. The hydrogen fuel is processed at the anode, where the electrons are separated from the proton on the surface of the Pt-based catalyst. On the cathode side, the precious metal combines with protons and electrons with oxygen to produce water. This process results in the generation of electricity, thermal power, and water. The net electrochemical reaction at the electrode is exothermic, which gives a positive cell potential as output. The electrochemical reaction that occurs at the electrode is summarized below:

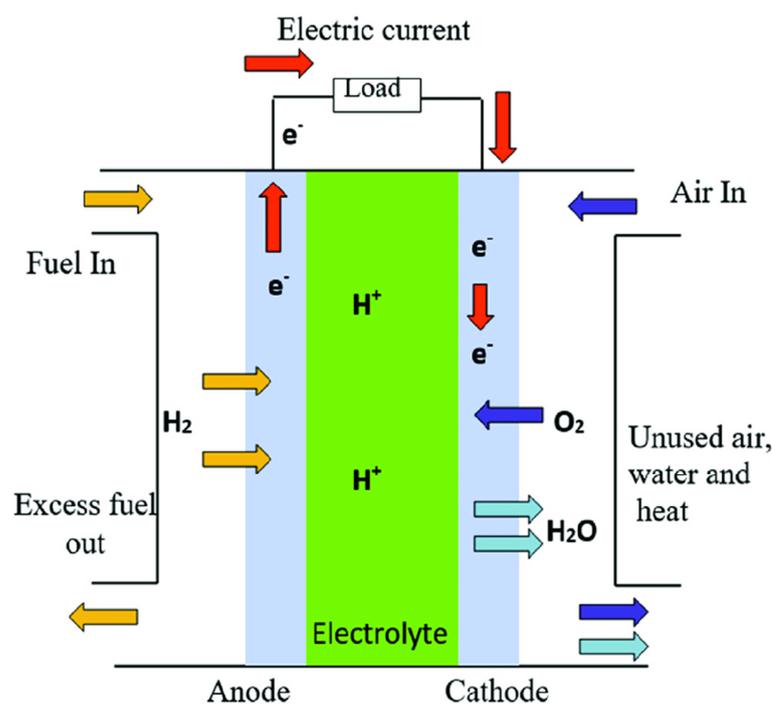
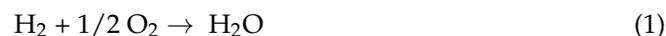


Figure 2. Schematic diagram for PEMFC [19].

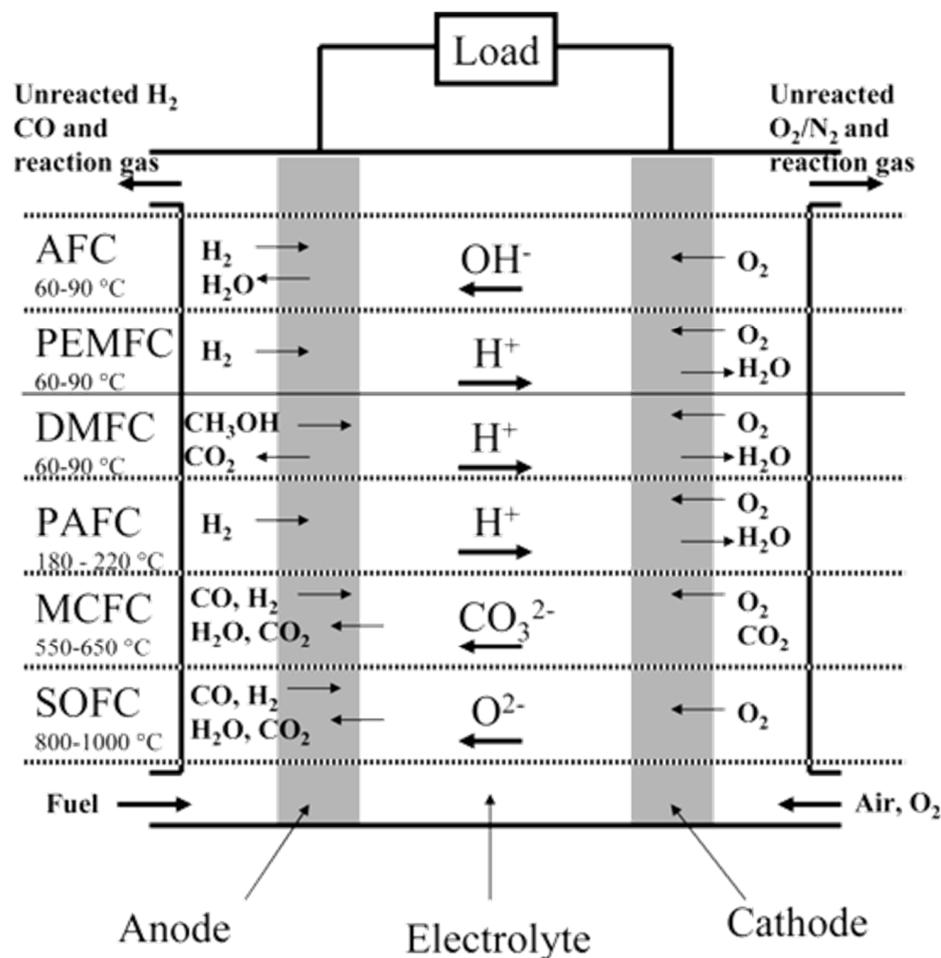
### 1.2. Types of FCs

Different factors may be used to classify FCs. To begin, they are divided into two groups based on the type of electrolyte utilized, which might be alkaline or acidic. Table 1 shows the typical characteristics of both types of FCs, organized by operating temperature. The efficiency of FCs is determined by the electrolytes and catalysts that are utilized and the operating temperature. Figure 3 depicts various electrode reactions that occur in various FCs.

**Table 1.** Characteristics of various FC systems [20].

Type	Anode	Cathode	Electrolyte	Working Temperature (°C)
AFC	Carbon (C)/platinum (Pt) catalyst		Aqueous KOH	Ambient–100
DMFC	C/Pt catalyst		Acidic Polymer	60–90
PEMFC	C/Pt catalyst		Acidic Polymer	Ambient–90
PAFC	C/Pt catalyst		Phosphoric acid in SiC matrix	150–220
MCFC	Ni	NiO	Molten $\text{Li}_2\text{CO}_3$ in $\text{LiAlO}_2^-$	550–700
SOFC	Ni-YSZ	LSM Perovskite	YSZ	600–1000

YSZ = Yttria-stabilized zirconia [21]. LSM = Strontia-doped lanthanum manganite [22].



**Figure 3.** Schematic diagram of electrochemical reactions occurring in various FCs [20].

One of the oldest FC types is the AFC [23–25]. The AFC was originally created for the Apollo missions [26]. A newer version was produced, which is still used to power shuttle flights. Potassium hydroxide is used as an electrolyte. Noble metal catalysts for both the hydrogen and oxygen electrodes are particularly active in the AFC. Alkaline electrolytes have easier H<sub>2</sub> and oxygen kinetics than acid electrolytes, resulting in greater cell voltages [20]. When using air, the AFC is subject to CO<sub>2</sub> as the contamination of the electrolyte, as well as sulfide and CO contaminants in the feedstock poisoning of the Ni and Pt catalyst. At 0.7 V, the AFC can provide up to 1 A/cm<sup>2</sup> [20]. The expected power output was achieved with development at 1–100 kW [17].

The PEMFC was originally designed for the Gemini spacecraft. Here, the electrolyte used is a proton-conducting polymer membrane, and the electrodes are constructed on a thin layer on either surface. In specific ways, the electrolyte is comparable to the plasticized electrolyte in a lithium-ion cell, which is made up of a liquid electrolyte trapped in a polymer matrix component [20]. It consists of a backbone made up of a solid PTFE with a perfluorinated side chain and a sulfonic acid group at the end. The proton species present in the acid group are dissociated and become solvated when the membrane is hydrated. Inside the polymer, the solvated protons are free and produce electrolyte conductivity [20,27–30]. PEMFCs are capable of having a power output of 1–300 kW with a high cost [17].

The DMFC is an environmentally acceptable energy supplier that undergoes methanol oxidation to convert chemical energy into electrical energy [31]. The DMFC is one of the most advanced FCs with respect to its performance and convenience of use, and it is being considered as a possible substitute for traditional batteries used in portable systems. These FCs are grouped under polymer membrane-based, low-temperature FC. This FC does not need alcohol to be reformatted into hydrogen species; instead, methanol is delivered straight to the FC. Because there is no reformer, the anode pulls hydrogen in a chemical process where methanol is dissolved in water, thereby decreasing the total expenditure. The DMFC has received considerable attention compared to other types of FCs because of its little noise, great efficiency, very low pollution, high dependability, and ease of upkeep. Methanol has a volumetric energy density of 17,900 kJ L<sup>-1</sup>, which is almost three times that of hydrogen [32]. Methanol is a popular fuel because of its cheap, high-energy density, transportation and storage convenience, and being capable of production from renewable biomass and natural gas means. As a result, DMFCs are ideal for electronic vehicles, portable electronic devices, and fixed purposes [33–37].

The PAFC is one of the most popular commercialized FC technologies among the several types of FCs [14,38–40]. Because of their mild working temperature, PAFCs have a long lifespan and a simple build. However, numerous drawbacks, including poor power density, limited lifetime, and high production costs, impede PAFC progress. This FC operates in the 423–493 K temperature range [41]. Immobilized liquid phosphoric acid and graphite-based electrodes serve as the electrolyte and prime cell parts of this FC, respectively. The PAFC has been in business for quite some time. The high-temperature PAFC exhaust gas can be utilized to generate extra electrical energy in other devices [39]. In delivering the power output, the PAFC has attained a fair development at 1–200 kW with high cost [17].

The MCFC can be used in energy storage [39,42–45]. The MCFC works efficiently at 560 °C, and the unwanted heat produced may be utilized in cogeneration. The MCFC system is more efficient than the PEMFC and the PAFC since it does not utilize noble metal catalysts. MCFCs are grouped as high-temperature FCs with a molten carbonate salt combination used as an electrolyte in a porous and chemically inert beta-alumina ceramic matrix [46]. A fuel electrode is made up of a porous nickel anode with dispersed aluminum or chromium for strength and sintering resistance, an oxidant electrode (lithium-doped nickel oxide cathode), and an LiAlO<sub>2</sub> matrix stuffed with lithium and potassium carbonates (62–70 mol percent Li<sub>2</sub>CO<sub>3</sub>) as the electrolyte make up the state-of-the-art MCFC. In addition, the fuel gas used is a humidified combination of H<sub>2</sub> and CO, and the oxidant is an assortment of O<sub>2</sub> and CO<sub>2</sub> that may have water vapor; the cell is operated at a pressure

and temperature of 1–10 atm and 650 °C, respectively [20]. In the case of power output, the MCFC can deliver 250–2000 kW with less life [17].

With  $O^{2-}$  conduction in the solid phase, the SOFC runs at 800–1000 °C. A sandwiched structure anode/electrolyte/cathode with diverse materials is always used in traditional SOFCs [47–51]. Due to the varied electrode materials, traditional SOFCs require at least two heating stages, resulting in high cost and energy consumption. The standard SOFC anode is Ni-YSZ cermet, which can readily cause carbon deposition or sulfur poisoning when utilizing hydrocarbon and sulfur-containing fuels [52]. SOFCs have two porous electrodes, i.e., both anode and cathode divided by a dense electrolyte. The cathode is involved in a reaction with electrons from the outside circuit; at the cathode, oxide ions are formed due to the presence of oxygen, which subsequently proceeds towards the anode via the electrolyte. The anode aids the reaction of oxide ions with carbon monoxide (CO) or hydrogen ( $H_2$ ), resulting in the formation of carbon dioxide ( $CO_2$ ) or water ( $H_2O$ ) and the release of electrons. The transport of electrons from the anode to the cathode is responsible for the creation of electricity. The cells function at 0.7 V and 1 A/cm<sup>2</sup> [20,53]. Furthermore, the major development in the SOFC with respect to power output has attained a range of 1–200 kW with high manufacturing costs [17].

### 1.3. Components of FC

#### 1.3.1. Electrocatalyst

A catalyst that is involved in an electrochemical process is known as an electrocatalyst. This sort of material may be created by packing nanostructured components into a catalytically active nanomaterial for electrocatalysis. Electrocatalysts ranging from Pt-group metals to C-based electrocatalysts have been created for both anodic and cathodic processes in various types of FCs [54–57]. For the evolution of sustainable energy technologies, the development of highly efficient and long-lasting electrocatalysts requires careful planning and synthesis. The nanoscale design, methods, and systems have various advantages, including novel reactions not achievable with bulk materials, shorter charge transport paths, and greater accommodation of the strain caused by electrochemical reactions inside electrodes. It is critical to employ innovative materials and technologies to increase the performance of sustainable energy conversion systems and fulfill the fast-growing energy demand. In addition to being low-cost, ideal nanostructure materials for electrocatalysis must have the following characteristics: large surface area, porous structure, high ion and electron mobility, large electrolyte–electrode contact area, high durability, and good thermal and chemical stability [31,58,59].

#### 1.3.2. State of Health of FC

Water exists in all areas of a fuel cell system's primary components as the principal product of activity. As a result, it is critical to control water transport in order to keep PEMFCs operating efficiently and reliably. There are various mechanisms of water transport in a PEMFC, including hydraulic permeation [60], electro-osmotic drag [61], thermal-osmotic drag [62], and back diffusion [63]. Because of the two-phase flow, water movements are difficult to monitor and forecast during operation. Nuclear magnetic resonance imaging and beam interrogation techniques such as X-ray neutron imaging and high-speed photography have been reported as methods of in situ observation of liquid water [17].

Fuel starvation occurs in a fraction of time interval, resulting in catalytic layer deterioration. Flooding and drying, which are common throughout operations, can reduce the performance of the fuel cell system [64]. Flooding can hasten the breakdown of a fuel cell system due to starvation and material changes. The drying process might cause pinhole deterioration of the polymer membrane. Flooding and drying are completely reversible with prompt interventions. CO poisoning also reduces the performance of fuel cell systems, and the reversibility is directly related to exposure time, temperature, and in-channel gas composition [65].

It is essential to develop techniques that are capable of perceiving glitches at the stack level due to vain conditions or material defects produced by aging during operation. Thus, the state of health of the FC can be studied with AI by investigating various input parameters such as cell voltage, current density, impedance spectra, magnetic fields, and acoustic emissions. Among these methods, a cell voltage measurement is considered the simplest because voltage drops that occur due to failures impose a rapid shutdown of the stack. Cell voltage is the sum of the reversible and significant irreversible voltages. The thermodynamics of the reactions, electrochemical kinetics, transport processes, and cell design all contribute to the cell voltage. Once the current is disconnected, the cell voltage is monitored as a function of time, usually for several milliseconds. Temperature, operating pressure, inlet humidity, and reactant concentrations are all kept constant. Moreover, there is a great demand for techniques that permit local measurement of PEMFC factors at the stack level to study localized aging events and investigate the degradation processes. For this reason, there are reports on in situ methods to calculate the current distribution over the cell surface. Current density is another important parameter used as an input. The current density is defined as the current produced by the FC per unit area of membrane-electrode assembly. We can estimate ohmic, concentration, and kinetic polarization losses and compare them to actual or theoretical values by fitting current density vs. voltage data to a simple empirical model.

The AC impedance approach, also known as electrochemical impedance spectroscopy (EIS), is being used by an increasing number of researchers in proton exchange membrane (PEM) fuel cell investigations. It has evolved to become the main research tool. EIS is mainly used as a reliable characterization tool to detect various failure mechanisms that can befall the fuel cell. The interconnection between EIS and the control approach of the required power converter offers the likelihood of predicting the online diagnosis of the fuel cell stack, not including any other sensor devices. Thus, the impedance spectra are considered an efficient input parameter for the state of health prediction of FCs. Moreover, there are reports on non-invasive methods in which the magnetic field produced by the change in induced current inside a stack is measured for the detection of faults in a PEMFC stack. For this method, the magnetic field produced is measured with the help of magnetic sensors placed around the stack.

The acoustic characteristics are another important factor in fuel cells that are essential for substantial progress in their model, control, robustness, and consistency. The electrochemical reactions that take place inside FCs are associated with energy transfer, where partial energy is converted into acoustic signals. The activity of the bubbles produced during the electrochemical reaction between the hydrogen and oxygen-producing water is the prominent acoustic source. The speed of the reaction has a better connection with the rate of formation of the bubbles. Consequently, the amplitude of acoustic emission is dependent on the rate of electrochemical reaction that will lead to a high rate of bubble formation.

The polarization curve, one of the most common ways to test a fuel cell, depicts the fuel cell's voltage output for a given current density loading. Polarization curves are often acquired using a potentiostat/galvanostat, which draws a constant current from the fuel cell and monitors the output voltage of the fuel cell. The voltage response of the fuel cell can be determined by gradually "stepping up" the load on the potentiostat. The degradation process in PEMFC can be studied using polarization curves (V-I curves), as shown in Figure 4. Based on variations observed in V-I curves at the time of FC operation, different losses, including Activation, Ohmic, and mass transport losses can be calculated. A fuel cell polarization curve has three distinct regions:

- At low power densities, the cell potential drops as a result of the activation polarization.
- Due to ohmic losses, the cell potential drops linearly with the current at moderate current densities.
- At high current densities, the cell potential drop deviates from the linear relationship with current density due to stronger concentration polarization.

The voltage overpotential necessary to overcome the activation energy of the electrochemical process on the catalytic surface is referred to as activation polarization. This polarization outweighs losses at low current density and measures the activity of the catalyst at a given temperature. Because the gaseous fuel, solid metal catalyst, and electrolyte must all make contact, this is a complicated three-phase interface problem. The catalyst lowers the height of the activation barrier, but the sluggish oxygen reaction causes a voltage drop.

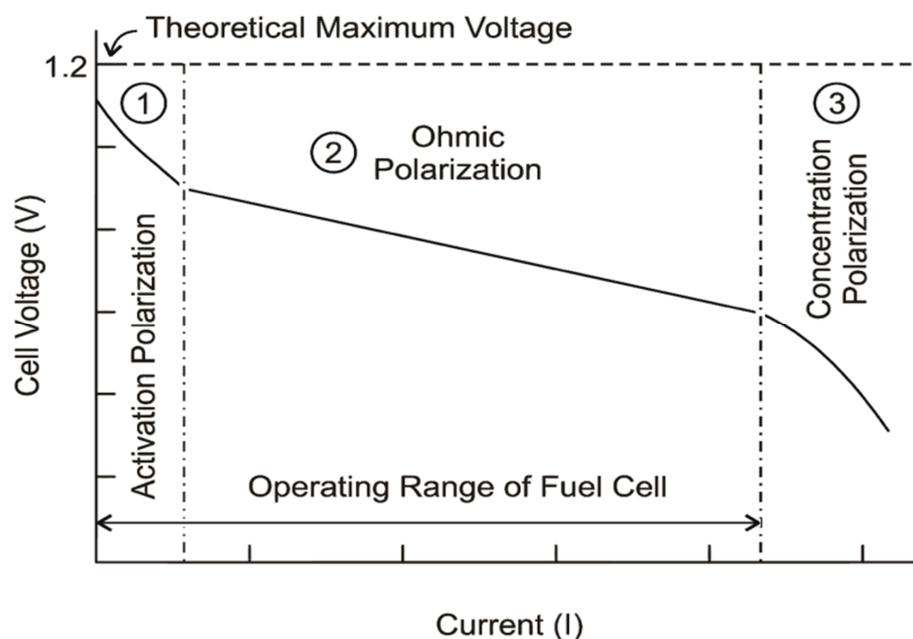


Figure 4. Polarization curves representing active, ohmic, and activation regions [66].

Conductors have an inherent resistance to charge passage, resulting in a decrease in cell voltage. This is known as “ohmic polarisation”, and it happens as a result of the electrical resistance in the cell components. The electrolyte, catalyst layer, gas diffusion layer, bipolar plates, interface contacts, and terminal connections are cell components that contribute to electrical resistance. Internal ohmic losses through the fuel cell dominate the voltage drop. This voltage loss is known as “ohmic loss”.

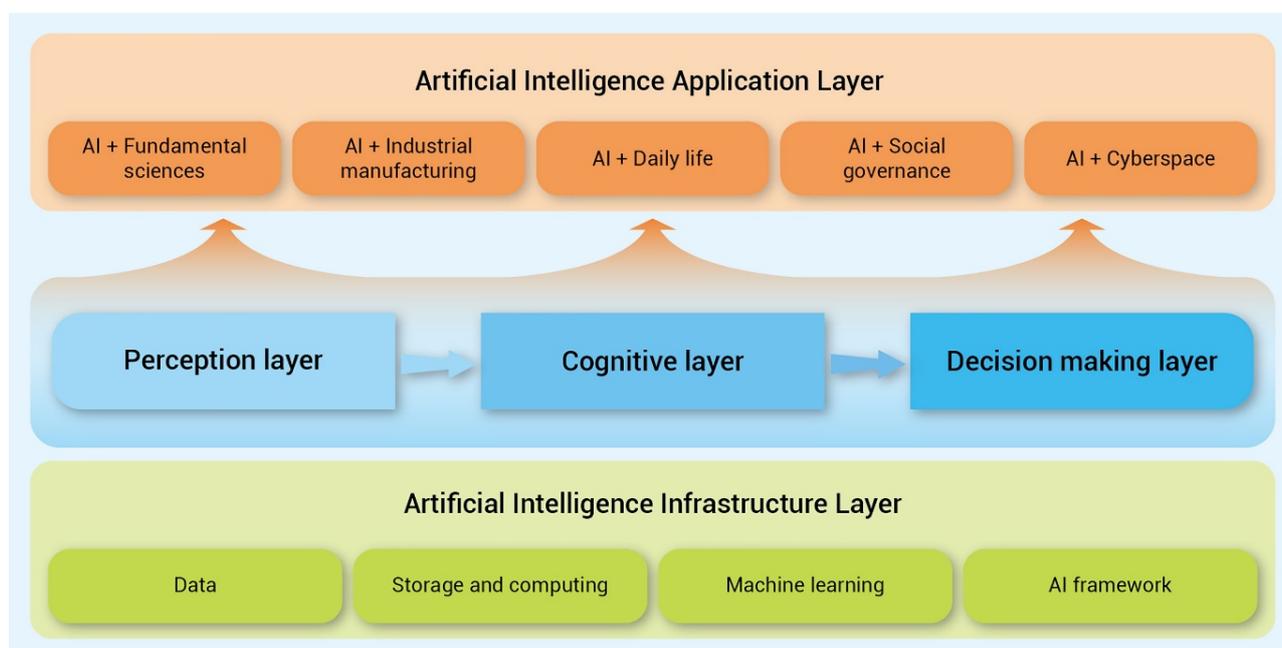
To generate electricity, a fuel cell must be constantly supplied with fuel and oxidant. To achieve optimal fuel cell efficiency, products must be continuously eliminated. The study of mass transfer of uncharged species is critical because it can result in severe fuel cell performance losses if not adequately understood. The concentrations of reactant and product within the catalyst layer determine fuel cell performance. By improving mass transport in the fuel cell electrodes and flow structures, concentration loss can be reduced.

#### 1.4. Artificial Intelligence (AI)

A significant concern in this paper is establishing the necessity for AI research in FC systems. AI combined with promising machine learning (ML) techniques well-known in computer science influences many parts of science and technology, business, and even our daily lives [67]. The ML approaches have been created to analyze high-throughput data in order to obtain meaningful insights and categorize, forecast, and make evidence-based judgments in unique ways, promoting the emergence of novel applications and fueling the long-term growth of AI [68]. The simulation of human intellect by a system or a machine is referred to as AI. The objective of AI is to create a device that can think and act like a person, including sensing, thinking, learning, planning, and forecasting. One of the key features that differentiate humans from animals is intelligence. With the inexorable occurrence of industrial revolutions, a growing number of machines replace human labor in all sectors of life, and the approaching replacement of human resources by machine intelligence is

the next major obstacle to be addressed. Many scientists are working on the topic of AI, resulting in a rich and diversified research environment [69–71].

Figure 5 depicts the general framework of artificial intelligence. Perceptual intelligence, cognitive intelligence, and decision-making intelligence are all part of the AI development process. Perceptual intelligence refers to a machine’s core human-like skills such as vision, hearing, touch, and so on. Cognitive intelligence is the capacity to think, infer, and acquire information at a higher level. It is based on cognitive science, brain science, and brain-like intelligence and aims to provide robots with human-like reasoning and cognitive abilities. Once a machine possesses perception and cognition abilities, it is frequently expected to make optimum judgments in the same way that humans do, improving people’s lives, industrial manufacturing, etc. To make optimum judgments, decision intelligence involves the use of applied data science, social science, decision theory, and management science. The infrastructural layer of AI, supported by data, storage, and processing capacity, ML algorithms, and AI frameworks, is necessary to realize the aim of perceptual, cognitive, and decision-making intelligence. It can then understand the internal rules of data for supporting and developing AI applications by training models. AI’s application layer is expanding and becoming more thoroughly interwoven with basic sciences, industrial production, human life, social governance, and cyberspace, significantly influencing our jobs and leisure [69,72–74].



**Figure 5.** The general framework of artificial intelligence [69].

Statistical learning, neural learning, evolutionary learning, and other learning theories are all used in AI. Neural learning is the most widely employed of them in a variety of applications. The most basic neural learning approach is the ANN. McCulloch and Pitts first introduced the ANN in 1943 with the concept of a mathematical model for a primordial brain cell (neuron) [75]. When the weighted sum of input reaches a threshold value, the neuron fires, resulting in an output as a response to an activated function. The ANN may change its settings to correct errors in the output, making it a more potent learning tool. In addition, approaches based on neural learning, statistical learning, and evolutionary learning were applied in a variety of practical applications. Bayesian and naive Bayes models [76], clustering [77], hidden Markov models [78], closest neighbor models [79], and other statistical learning techniques are used in AI. Genetic algorithm (GA) [80], particle swarm optimization (PSO) [81], ant colony optimization (ACO) [81], bee algorithms, and other evolutionary learning approaches are also popular. In recent years,

hybrid AI approaches have been utilized in various applications to achieve more accuracy than could be accomplished with a single method.

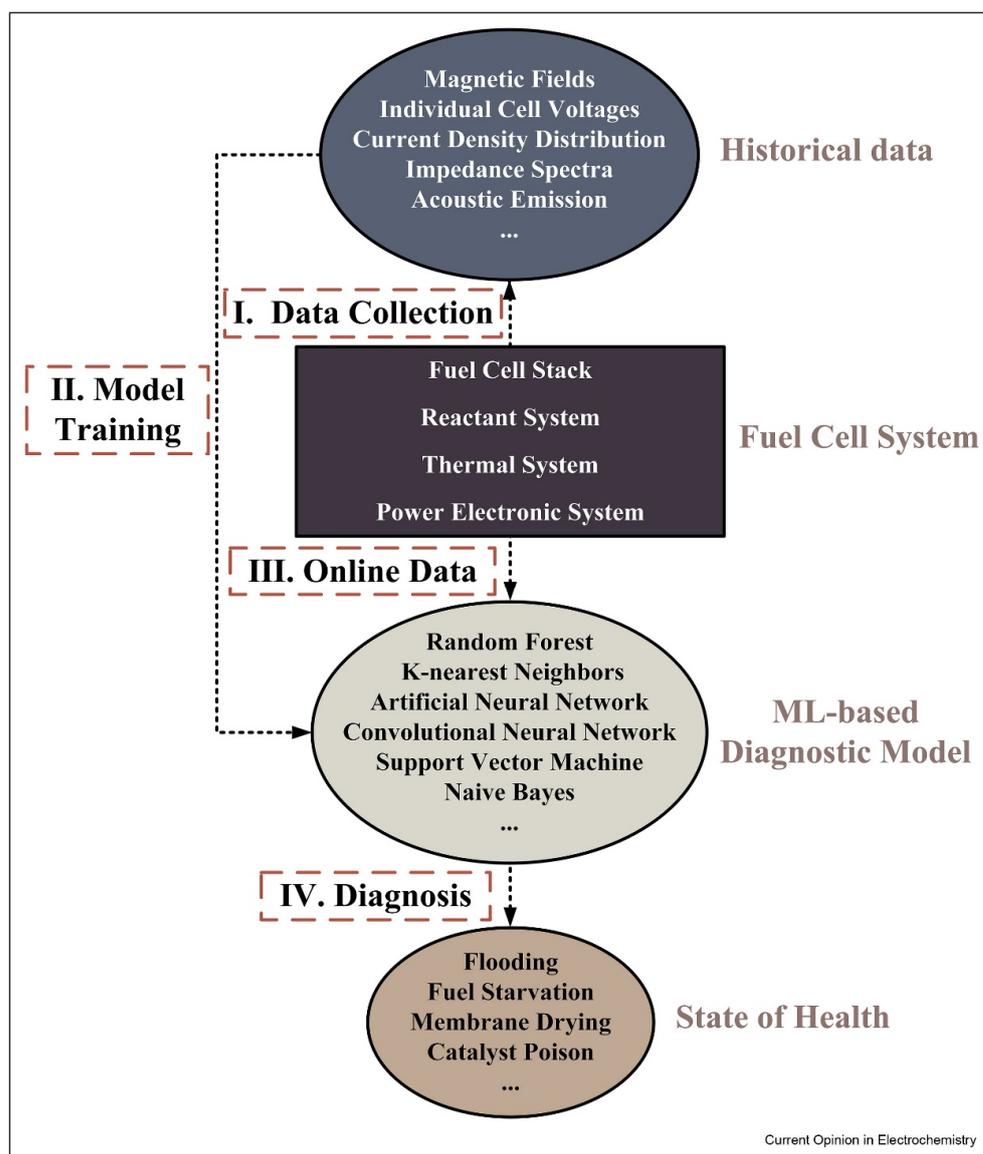
ML is a method of obtaining models from data or interactions with the environment using an algorithm that can then be performed automatically with minimum human intervention. Unsupervised, supervised, and reinforcement learning are the three types of machine learning [82]. Unsupervised learning utilizes simply unlabeled data sets, supervised learning utilizes labeled data sets, and reinforcement learning necessitates active interaction with the environment. The challenge of optimizing long-term rewards is addressed through reinforcement learning. Unsupervised learning is concerned with how the data are distributed. Clustering is a typical approach for grouping data items with similar traits or attributes. A regression problem occurs when the label has a continuous value in supervised learning, whereas a classification problem occurs when the label has a discrete value. As a result, data-driven defect diagnosis might be classified as a problem.

Figure 6 depicts a simple procedure for using ML to diagnose FC faults. Experiments must be carried out in various operating situations, including fault-free and other defective states of interest, throughout the data collection stage, and the mechanism of imposing faults must be carefully designed. Then, the ML-based diagnostic model is trained, and the signal-to-SoH link is established. Finally, the model may be used to monitor SoH in an FC system. The signals and the diagnostic model are the two most important variables, as indicated in Figure 5. Under the premise of detecting defects, diagnostic signals should be as basic as feasible [83].

ML has been utilized to construct surrogate models for sensitivity studies, battery health monitoring, and inverse parameter estimation for FCs and batteries [84]. The techniques used in these models include linear regression and artificial neural networks (ANN). They are usually used to forecast a single scalar or a limited number of scalar outputs from the original model. ML has also been used to analyze experimental data, for example, to improve designs and examine long-term battery performance. Recently, deep learning networks have gained popularity as FC and battery surrogate models [85]. The types of hidden layers employed differentiate deep networks. Convolutional neural networks (CNNs) have been used to forecast stack voltages and polarization curves in PEMFCs [86], while recurrent neural networks (RNNs) have been used to anticipate functionality decline [87]. Other uses include flaw categorization in FC and water management systems and surrogates for mesoscale simulations [88].

Several internal and external factors play a crucial role when operating the FC experimentally, and it is tough to spot faults. It is tough and expensive to analyze its overall performance using experimental settings. Furthermore, predicted outcomes may not always be supplied. As a result, a unique tool has been developed among researchers, which may cut costs and ensure redundant and repeatable trial results. These requirements are met to a large extent when the FC is developed utilizing AI techniques. In fact, creating a reliable model that can forecast the performance of anode and cathode electrodes based on cell operating temperature and the applied voltage is critical. A powerful AI tool can be used to create a model for forecasting the performance of FC devices. Predicting the performance of FCs is crucial for their effective usage. As a result, creating a suitable model with a variety of input parameters is a complicated process. Thus, we discuss various AI approaches to investigate the ideal operating parameters of FCs for obtaining the highest performance efficiency (current and power density) from the design, electrodes, and electrolyte materials used in FCs.

The main objective of this review paper is to investigate various AI tools such as artificial neural networks, genetic algorithms, particle swarm optimization, random forest, support vector machine, and extreme learning machine for fuel cell diagnosis. Research papers that emphasize the state of health of FCs are given more focus so that FC fault detection can be done in an efficient way using AI tools.



**Figure 6.** A flowchart depicting the use of machine learning-based diagnostic approaches on a FC system [83].

## 2. Methodology and Structure

This review includes an introduction, which elaborates the description of FCs (its components and various types) and artificial intelligence. This section portrays a clear idea about the need for AI in the field of the FC. This review article is divided into five parts. After the introduction in the previous section, the methodology and structure are included in this section. Section 3 deals with various types of common AI tools used in the field of FCs such as artificial neural networks, genetic algorithms, particle swarm optimization, random forest, and support vector machines. Finally, the summary and future outlook are included in Section 4.

## 3. Common AI Methods Used in FC

In its classic terms, AI refers to the use of a computer to make computations that are similar to those performed by a human. The machine analyzes inputs and provides outputs for a variety of scenarios that the user defines using code/algorithms. AI is a revolutionary technology that has the potential to provide value in four areas: demand forecasting, supply chain optimization, and research and development optimization; producing lower-cost,

better goods; delivering competitively priced goods and services to the proper clients; and improving the customer experience.

The key issues that are focused on in this review include a novel optimization method for automatically collecting characteristics from the impedance spectra of the polymer electrolyte membrane, determining the voltage and current of a PEMFC, performance, and durability of an FC by predicting the local current distribution, energy management strategy, optimal power allocation between the FC and the battery system, controlling the flow channel design and voltage degradation for PEMFC, etc.

### 3.1. Artificial Neural Network

Artificial Neural Networks (ANNs) are based on neuroscience principles and use models inspired by the human brain's neural network. An input layer, hidden layer(s), and an output layer make up an ANN. The input layer is where information is supplied to the program, and the output layer is the outcome of the ANN computation, as their names suggest. The computation is carried out in a single or several hidden layers, effectively "black boxes" that build relationships between system parameters, and information flows from one hidden layer until the output layer is reached. Each layer has its own computational units, suitably named neurons, linked by weights to each neuron in the preceding and succeeding layers. Based on a study of the importance, bias, and input signals, ANNs make decisions, and information flows from one level to the next within the network [89]. Backpropagation allows ANNs to self-correct, which is what makes them such a powerful tool. ANNs also avoid solving difficult differential equations by attempting to anticipate the outcome while changing the input parameters at the same time. Single-layer feedforward networks, multi-layer feedforward networks, and recurrent networks are the three most common network architectures. The schematic diagram representing an ANN model is shown in Figure 7.

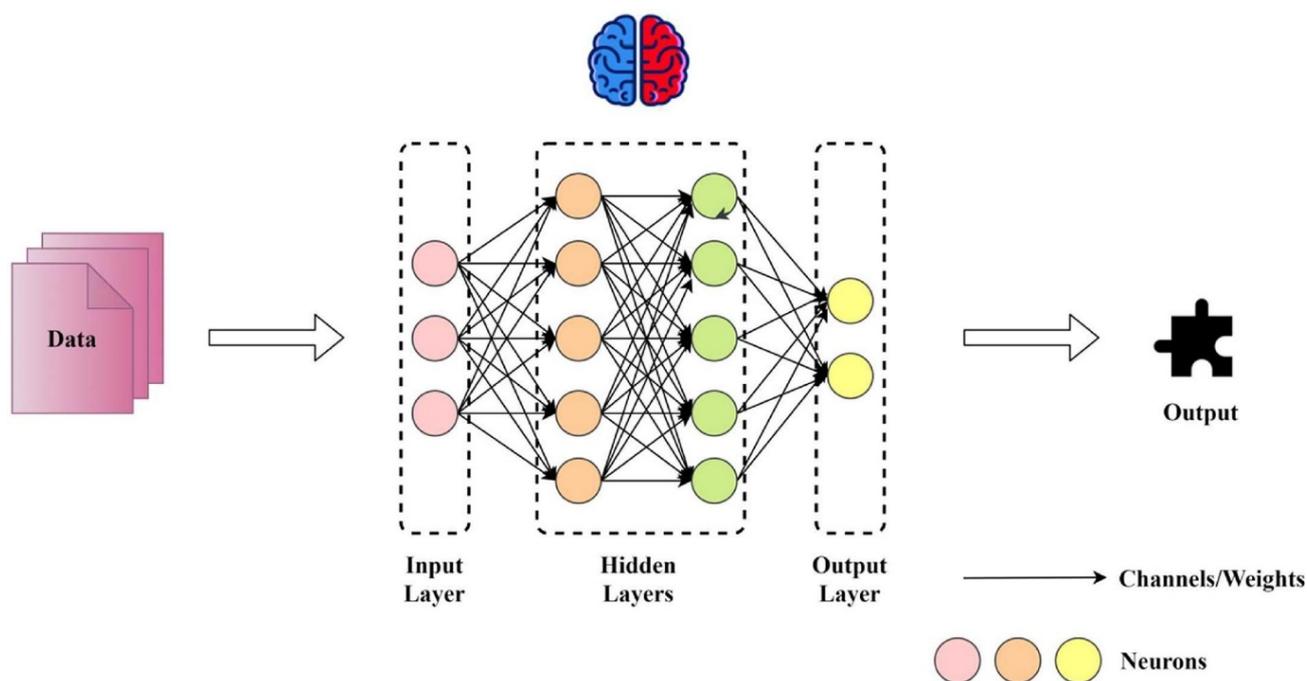


Figure 7. Schematic diagram of an ANN [89].

Marek Gnatowski and their co-workers investigated numerical simulations of transport events within a solid oxide FC anode [90]. The observed and projected overpotentials differ significantly when using the standard mathematical approach. In the electrochemical reaction model, a modified formulation of the issue incorporates data-driven modification of reaction charge transfer coefficients. The team provided a customized computational

technique in which an artificial neural network changes charge transfer coefficients based on operating circumstances and the datasets available. The neural network was trained using twelve experimental data points from the literature for an anode's polarization curve. The training set included the dataset for the anode operating at two distinct temperatures, 800 °C and 900 °C. An additional six data points for an anode operating at 1000 °C were included in the test set. The Artificial Neural Network presented charge transfer coefficients as a functional relationship between temperature and withdrew current. The projections' outcomes are compared to experimental data from the literature. The obtained findings show that the nonlinear functional relationship between the transfer coefficient and the withdrew current and the linear relationship between the transfer coefficient and temperature have the least difference between experiment and simulation. It was demonstrated that the grey-box technique might be used to increase prediction accuracy in SOFC modeling. The Artificial Neural Network was proven to enhance an electrochemical process model in solid oxide FC modeling.

Using green and carbon-free energy sources is a novel idea in the energy conversion, power generation, and energy management framework. Because neural network applications in the field of FCs are limited, particularly in the case of solid oxide FCs, Xinxiao Chen et al. used an ANN model to simulate objectives based on empirical information [91]. A new optimization approach is also used to improve the efficiency of solid oxide FCs. The grey wolf optimizer with quick, robust, and simple characteristics is used to determine the best operating variables of solid oxide FCs. The thickness of the anode layer, electrolyte layer, and cathode layer and the pores of the anode layer are the essential operational parameters employed in the optimization. The modeling findings were compared to test data, confirming the ANN model and optimization method's capacity to identify parameters. Two case study optimization methods were evaluated. To begin, the electrolyte layer thickness, anode support layer thickness, cathode thickness, and anode support layer porosity were optimized at an operating temperature of 800 °C, yielding values of 19 µm, 0.52 mm, 62.16 µm, and 75 percent, respectively. In the second scenario, the proposed strategy increased the power density by up to 28%, close to the initial experimental results. The grey wolf optimizer (GWO) is used to determine the SOFC's optimal variables based on operational points. As a result, the recommended technique may be utilized to accurately estimate and specify the SOFC's ideal characteristics. It is worth noting that the ANN with GWO technique ultimately cuts production costs while also minimizing the need for substantial experimental effort.

A strategy for automatically extracting features from polymer electrolyte membrane FC impedance spectra is proposed by Antonio Guarino and co-workers [92]. The researchers employed an artificial neural network that was trained using the similarity learning technique. The network learns the characteristics of impedance spectra and maps each one into the embedding space by properly grouping them and emphasizing differences between spectra belonging to distinct faults. The topology of the Siamese network is optimized, and the quality of the learned representation is assessed by examining the clusters found in the feature space. The experimental spectra dataset has been supplemented in two methods, with the results contrasted. A complete framework for PEMFC diagnosis has been developed in this research, based on impedance spectra and featuring an automated features extraction process. The features are retrieved using an ANN-based embedding function that is created and trained using an SNN structure in the context of similarity learning. In comparison with existing state-of-the-art feature extraction approaches, the suggested strategy performed better. Compared to the top-performing state-of-the-art features extraction technique, FastICA, the recommended SNN strategy improves the AMI clustering score by 30 percent. The classification is also reduced because of the good clustering result, and a simple closest neighbor classification yields an F1 score of 0.909.

Polarization curves are still one of the characteristics used to examine the effectiveness and durability of fuels. The use of an ANN to calculate the voltage and current from a PEMFC with a membrane area of 11.46 cm<sup>2</sup> was investigated by Tabbi Wilberforce and

A.G. Olabi [93]. For the estimate of the current and voltage acquired from the PEMFC under consideration, performance prediction for the group method of data handling (GMDH) as well as feedforward backpropagation (FFBP) neural networks were used. Even though the GMDH neural network performed better than the FFBP neural network, the study revealed models with good predictions. According to the study, the GMDH neural network is proposed as the best model for forecasting the performance of a PEMFC. It was also discovered that increasing the reactant flow rate has a direct influence on the FC's performance but that this is proportionate to the total irreversibilities in the cell; therefore, in order to run the FC cheaply, the hydrogen flow rate must be reduced. As a result, the pumping energy needed for fuel flow will be reduced, lowering the net loss in the cell.

Understanding the local current distribution is critical in the construction of an FC to gain greater performance and durability. As a result, several developers use a segmented FC to monitor current distribution under different operating situations. Experimental data are obtained using the program. Jin Young Park et al. proposed a way of utilizing the obtained data to construct a local current prediction model [94]. This neural network-based forecast is described in-depth, including the data pre-treatment. Current residual values are employed in the pre-treatment procedure to improve prediction accuracy. Consequently, the model had 2.98% inaccuracy in predicting local current values. Pressure, temperature, cathode relative humidity, and cathode flow rate influences on local current distribution patterns are investigated using the model. Because an FC's non-uniform current distribution frequently results in poor performance or rapid local deterioration, an extra model is used to determine the best operating conditions for achieving current uniformity. The local current prediction model's inputs and outputs are switched to create this model. Under the current load at 1 A/cm<sup>2</sup>, the uniform distribution is accomplished using the model application with a standard deviation of 0.039 A/cm<sup>2</sup>.

### 3.2. Genetic Algorithm

However, regardless of its good global search speed and cheap algorithm complexity, the genetic algorithm (GA) in evolutionary computing has become one of the most concerned algorithms among modern optimization algorithms. The GA is a technique of random search based on biological evolution. Professor Holland of the University of Michigan was the first to suggest this viewpoint in 1975 [95]. It has implicit parallelism built-in and may act directly on structural items without being constrained by function continuity. The GA can automatically update the progeny of optimization outcomes and global search direction using roulette and other ways. The GA is frequently utilized in discrete optimization, algorithm learning, data processing, and other domains due to these advantages.

GAs were created to simulate natural processes required for evolution, particularly those that follow Charles Darwin's ideas of evolution and natural selection. For the purpose of addressing a problem, GAs replicate the survival of the fittest among individuals over several generations. Each generation is made up of a population of character strings that resemble the chromosomes that make up human DNA. Each person symbolizes a possible solution and a point in a search space. Individuals in the population are then forced to go through an evolutionary process [96].

GAs are built on the following bases analogous to the genetic structure and behavior of chromosomes within a population of individuals: Individuals battle for resources and mates in a population. Individuals who compete well will generate more offspring than those who perform badly. Because good genes spread across the community, two good parents can occasionally create offspring who are better than either parent. As a result, each generation will become more adapted to their surroundings [96].

PEMFCs are thought to be capable of replacing conventional internal combustion engines in vehicles due to their high efficiency, lack of emissions, minimal noise, and other benefits. The creation of an energy management system becomes the object of study in

order to extend the lifetime of FCs. The energy management approach of an FC hybrid electric vehicle with an FC as the primary power source and a battery as an auxiliary power source is discussed by DehaoMin and colleagues [97]. A novel algorithm is presented after existing research is summarized. Because frequent startup, shutdown, and load changes can shorten the life of an FC, it is important to prevent these as much as possible. The proposed study presents Neural Network Optimized by Genetic Algorithm (NNOGA) as a viable method for the analyzed system for this goal. The neural network may be trained appropriately using a genetic algorithm, and the trained network can deliberately avoid particular outputs based on the criteria. The network may consciously prevent wasteful start-stop and quick load shift, thanks to the optimization ability of the Neural Network Optimized by Genetic Algorithm, which can modify the preference of the trained neural network. As a result, the FC's lifespan is extended. The suggested algorithm's validity is confirmed by simulation and comparison testing.

A prospective hybrid power system for emerging energy generation applications is the polymer electrolyte membrane FC combined with a battery. The energy management strategy (EMS) has a big impact on FC longevity, battery charge maintenance, and fuel usage. Hai-BoYuan et al. proposed a GA-based optimized rule-based EMS for efficient power allocation between the FC and the battery system [98]. Control variables in real-time rule-based EMS are optimized to maintain battery charge while taking FC durability and efficiency into account. MATLAB/Simulink and a LabVIEW-based experimental rig are used to simulate and experimentally verify the proposed improved rule-based EMS. In addition, the traditional rule-based EMS, fuzzy logic EMS, and dynamic programming (DP) EMS are compared. The comparative findings show that the optimized rule-based EMS outperforms the conventional rule-based and fuzzy logic EMSs by a significant margin. In terms of fuel economy, battery charge sustenance, FC efficiency, and system longevity, near-optimal performance is validated when compared to DP EMS. The integration of rule-based EMS and GA optimization algorithms has the benefit of expert experience and global optimization properties, allowing for optimized power allocation in practical uses with less computation strain. It can be easily implemented in other EMS systems without losing authenticity.

To achieve the best performance of PEMFCs, an effective strategy for guiding the flow channel design of the bipolar plate (BPP) must be developed for the PEMFC. Most previous research has concentrated on improving constant channel dimensions and structures without taking into account the flow channel's ideal local performance. The down-the-channel performance model and the GA are used by Zihan Zhou and his team in work to improve BPP channel/rib patterns for FCs [99]. A flow channel is partitioned into numerous segments, with the channel dimensions of each segment being included as variables in the down-the-channel performance model to produce the best parameter design via the GA. The CFD and local current density experiment confirm the model and optimization findings. Both CFD and local current density experiment findings are inconsistent with the result of the down-the-channel performance model. The cell efficiency of a variable rib-to-channel width ratio (RCWR) design along the flow channel is found to be superior to that of a constant RCWR design. When the sum of rib and channel width (SRCW) is larger, and the output voltage is lower, performance gains are more noticeable. Design guidance for the cathode flow channel RCWR is offered from upstream to downstream.

The flow channel arrangement of high-temperature polybenzimidazole (PBI) proton exchange membrane FCs (HT-PEMFCs) doped with phosphoric acid significantly impacts their performance. Taiming Huang and colleagues used a GA to optimize the flow channel of a high-temperature PEMFC [100]. The genetic algorithm is used in this study to optimize the initial three-dimensional simulation model by determining the best channel arrangement. To improve HT-PEMFC performance, make the widths of the top and bottom borders of the anode/cathode flow channels independent variables with a defined range. The objective function is specified to be the ratio of pressure drop loss to HT-PEMFC output power. The widths of the top and bottom margins on the anode side are 0.513 mm

and 0.635 mm, respectively, and 0.752 mm and 1.159 mm on the cathode side. The flow channel's cross-sectional shape is trapezoidal, which provides the highest performance. The limited contact surface between the flow channel and the GDL on the anode side might speed up hydrogen diffusion. The more contact surface generated by the flow channel and the GDL can deliver more gas for the electrochemical reaction at the cathode. At 0.4 V, the optimum model's pressure drop loss and output powers are 1.7% and 6.5% higher than the original model's, respectively. The findings may help to enhance the design and operation of future HT-PEMFCs.

Prognostics can anticipate the breakdown of a PEMFC and help create a management plan to extend its life and improve its performance. Using a unique prognostics technique based on GA and an extreme learning machine (ELM), the voltage deterioration for PEMFC under various scenarios is forecasted by K. Chen et al. [101]. The new prognostics technique takes into account the impacts of PEMFC load current, relative humidity, hydrogen pressure, and temperature on PEMFC deterioration. To begin, the ELM creates a voltage decay prediction model for PEMFC. The GA is then used to find the best parameter for the suggested deterioration prediction model. Finally, the suggested prognostic method's voltage degradation prediction is proven by utilizing data collected from the PEMFC in an actual postal FC electric vehicle (PFCEV) under real settings and PEMFC at dynamic load current. The experimental findings demonstrate that the proposed prognostics technique can accurately estimate PEMFC voltage deterioration in PFCEV under real-world conditions. Other standard data-based prognostics approaches fail to predict voltage deterioration for PEMFC under dynamic load current and the suggested method.

### 3.3. Particle Swarm Optimization

Particle swarm optimization (PSO) is an evolutionary computer method for optimizing continuous nonlinear, constrained, unconstrained, nondifferentiable multimodal functions. The process of finding the most appropriate solution to accomplish the "best" aim in a situation is known as optimization. Its goal is to find the best answer possible. Several optimization techniques, particularly meta-heuristic algorithms, have been tried in recent years to improve the solution of application or theoretical issues. PSO is one of the most often utilized algorithms. Eberhart and Kennedy presented it in 1995 as an evolutionary algorithm [81].

PSO is based on two sources: first, generic artificial life, such as bird flocking, fish schooling, and human social interaction, and second, random search methods in evolutionary algorithms. Animals, particularly birds and fish, always travel in groups to avoid clashing; each member follows its group and adjusts its position and velocity based on group knowledge, reducing individual action in the search for food, shelter, and other necessities. PSO has now become one of the most popular methods for solving optimization issues. It imitates the swarm behavior of various animals, such as flocks of birds, fish schools, and mammal swarms. These species' swarm behavior helps them avoid dangers and find food, among other things. This swarm's particles communicate with one another and make decisions in concert. Human beings have their own prior experiences, ideas, and work rules, which they use to guide their behavior (individual best position). Humans also follow the path defined by the society/group, which is believed to be the ideal for the entire group (global best position).

For the long-term functioning of PEMFCs, degradation prediction is an important strategy. A unique grey neural network model (GNNM) technique is described by KuiChen et al., where GNNM is integrated with particle swarm optimization (PSO) and the moving window method to anticipate the deterioration of PEMFC under various operating situations [102]. The impact of load current, intake temperature, inlet hydrogen pressure, and inlet relative humidity is taken into account in the suggested technique. A grey neural network is used to create PEMFC's deterioration prediction model. The PSO optimizes the initial weight and threshold of established GNNM. The optimized PSO-GNNM is repeatedly trained using the moving window approach with multiple newly observed data.

The impact of various moving window widths on PEMFC deterioration prediction under static load current is examined. After that, a comparison is made between the suggested approach and the adaptive neuro-fuzzy inference system method. Furthermore, the effect of load current on the deterioration forecast of PEMFCs in real-world postal FC electric vehicles is investigated. Finally, three PEMFC aging tests under various circumstances are used to validate the suggested approach. The findings demonstrate that the recommended technique can accurately predict PEMFC deterioration in a variety of applications.

Because of their high energy conversion efficiency, high power density, and low operating temperatures, polymer electrolyte membrane FCs are commonly used in engineering applications. They have recently gained prominence in vital and strategic applications such as electric automobiles and unmanned aerial aircraft. However, FCs are used in a variety of applied-theoretical investigations. Models that are highly comparable to the genuine PEMFC should be employed to improve the accuracy of this research. Modeling of PEMFC with chaos-embedded particle swarm optimization for optimum parameter estimates was reported by Mahmut TemelÖzdemir [103]. This research introduces a novel objective function to more authentically determine the unknown variables of PEMFC heaps. Three commercially available PEMFC stacks, the 250 W Stack, BCS-500 W, and Nedstack PS6, were numerically simulated to demonstrate the efficiency of the proposed methods for parameter determination.

Identifying sustainable approaches is difficult due to the negative environmental effect and increasingly diminishing supply of fossil fuel-based energy sources for power generation. The ever-increasing global population expansion, which demands a greater level of life, complicates this issue. An FC system may generate power and water more efficiently while emitting almost no carbon dioxide. Internal limits and operational characteristics such as temperature, hydrogen, oxygen partial pressures, and humidity levels cause a nonlinear power characteristic in a typical FC stack, resulting in lower overall system performance. Consequently, it is critical to extract as much power as possible from the stack, thereby reducing fuel consumption. To keep the output power of an FC stack incredibly close to its peak, Doudou N. Luta and their group investigated and contrasted two maximum power point tracking (MPPT) techniques, one based on the Mamdani fuzzy inference system and the other on the particle swarm optimization (PSO) algorithm [104]. To do so, the inverter connected to the FC unit must be able to continually self-modify its parameters, adjusting its voltage and current in response to the location of the maximum power point. As there are other approaches to designing a maximum power point tracker, this work examines the response characteristics of a Mamdani fuzzy inference engine using the particle swarm optimization methodology. A 53 kW PEMFC was used in the study, which was connected to a DC-to-DC boost converter that provided 1.2 kV from a 625 V input DC voltage. A Matlab/Simulink environment was used to complete the modeling. Compared to the Mamdani controller, the MPPT controller based on the PSO algorithm demonstrated superior tracking efficiency. Moreover, the PSO controller's rise time was somewhat shorter than the Mamdani controller's, and the PSO controller's overrun was 2% less than the Mamdani controller's.

Upasana Sarma and Sanjib Ganguly proposed an optimization technique for scaling the modules of a PEM FC (PEMFC)-battery hybrid energy system (HES) to provide the necessary driving force to transport passenger trains [105]. The goal is to reduce the cost of HES while staying within the limits of the battery state-of-charge limit, PEMFC capacity constraint, and instantaneous power balancing constraint. A PEMFC-battery HES model appropriate for locomotive use is developed. To establish a balance between instantaneous power demand and power supply, two energy management systems (EMS) are presented. The particle swarm optimization-based solution algorithm incorporates the EMS effectively. The simulation research employs three real-world driving cycles. According to the simulation research, the size of the PEMFC and battery is determined by the EMS, average train speed, and slope of the railway track. The selection of EMS has an impact on fuel usage and dynamic behavior.

To simulate and study the dynamic conversion behavior of a solid oxide FC (SOFC), it is critical to identify trustworthy and precise parameters. To handle the parameter identification problem of SOFC models, a simplified variation of competitive swarm optimizer (SCSO) was presented by G. Xiong and the team [106]. CSO excels at unimodal optimization issues in particular. However, when addressing complicated multimodal optimization issues, it has the downsides of “two steps ahead, one step back” and diverting from the promising approach, resulting in low searching efficiency. To overcome these disadvantages, SCSO uses two simple components: a simplified learning equation, according to which losers only learn from winners, ignoring the population’s mean position, and a refreshed approach to random numbers, according to which random numbers are renewed for each loser rather than for each dimension of each loser. A Siemen Energy cylindrical cell and a 5-kW dynamic tubular stack receive SCSO treatment. Furthermore, the effect of the weight parameter and the advantage of simpler components were experimentally explored. Compared to other sophisticated algorithms, the results show that SCSO is very competitive in terms of precision, stability, convergence, and statistics.

### 3.4. Random Forest

Random forests (RF) are a widely used ensemble learning technique with many implications in data mining and machine learning. Random forests are a nonparametric tree-based collective solution for effective data-adaptive inference that combines the notions of adaptive closest neighbors and bagging. The greedy characteristic of one-step-at-a-time node division allows trees/forests to enforce regularization for successful analysis in “large  $p$ , small  $n$ ” issues, and the “grouping property” of trees allows RF to handle correlation and interaction among variables with ease.

The Random Forest approach combines the bagging algorithm with a multilevel decision tree, which is frequently used to select features in the development workflow of data-driven models. The rationale is that random forests’ tree-based methods are essentially ranked by how efficient they increase node purity. Figure 8 depicts the random forest formation process [107].

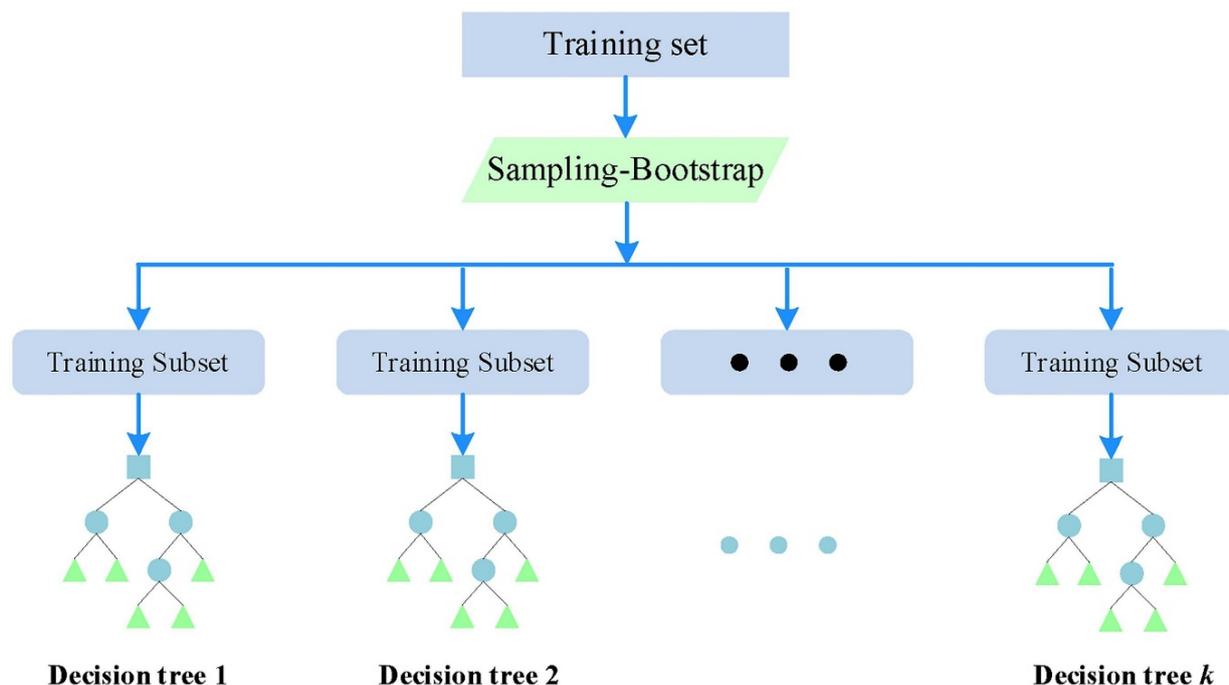


Figure 8. Schematic diagram representation of the random forest formation process [99].

Several diagnostics approaches based on the previous hydrogen FC status data are presented to determine the health state of hydrogen FCs. Because a variety of variables might

cause the FC problem, feature selection would be required during diagnostics. RH Lin et al. attempted to produce the required features using an upgraded PCA technique [108]. Based on these attributes, a random forest algorithm is built to forecast health status based on historical data. In this study, all hydrogen FC sensor data elements were monitored and used statistical analysis to extract many properties. The authors present a hydrogen FC diagnostics model that is both efficient and accurate.

SOFCs are complicated systems in which gas-phase mass movement, heat transfer, ionic conduction, chemical reactions, and electrical conduction all happen at the same time. To regulate and optimize their operations, trustworthy simulation tools are required. ML is a technique for swiftly estimating and generalizing the relationship between input and output values in a process. Modeling, simulation, optimization, control, signal processing, pattern recognition, and systems like electricity, production, and renewable energy systems all employ ML techniques. Many strategies aid in the development of successful algorithms for SOFC systems. Few academics, however, have looked into and compared regression techniques. Research done by F.C. İskenderođl and colleagues compared two efficient ML techniques, Random Forest (RF) and Support Vector Regression (SVR) [109]. These methods are used to forecast SOFC cell performance. The algorithms were developed based on experimental data collected at various temperatures and hydrogen flow rates. Furthermore, the influence of the quantity of pure hydrogen and the total amount of hydrogen in the fuel mixes given to the SOFC's anode side on the experimental voltage was compared. The experimental data collection that was utilized to create the model contains 1272 records about SOFCs that were operated under various operating circumstances. The regression methods indicated above are trained using 1122 records from the experimental data set. Consequently, the algorithms are put to the test, and the experimental data are compared to the findings provided by the algorithms in order to validate forecast outcomes. With typical absolute percentage errors of 1.97 percent for the RF method and as low as 0.92 percent for the SVR algorithm, the model predicts cell performance (output voltage) in about 0.52 s. The SVR algorithm is chosen as the most plausible model in this paper. When the created models have been demonstrated to be reliable and precise after testing with unknown data, the impacts of process factors on the fluctuation of the SOFC output voltage may be investigated.

Because of their clean and efficient functioning, PEMFC stacks are frequently employed in mobile and portable applications. To enhance the deterioration prediction of a PEMFC stack, FK Wang et al. presented an ensemble model based on a stacked extended short-term memory model that integrates three machine-learning models, including long short-term memory with attention mechanism, support vector regression, and random forest regression [110]. The dropout approach was used to calculate the prediction intervals. Using two PEMFC stacks, the suggested model is compared to various current models. According to the findings, the presented model beats the previous models in terms of mean absolute percentage error and root mean square error. The proposed model using the sliding window technique can deliver superior results in terms of residual usable life prediction.

The system energy optimization was investigated by X. Lü and colleagues using a thorough performance assessment and random forest prediction approach in order to enhance the stability, real-time performance, and economy of the PEMFC hybrid welding robot system [111]. The optimal control strategy was built on the basis of rule partition, using the entropy weight technique and the cloud model comprehensive performance testing procedure; the random forest prediction method was implemented in the energy management system, and the model parameters with the least mean square error were determined using particle swarm optimization, and the robot's load power was estimated. Finally, the assessment findings are used to determine the expected ability to enhance and optimize the hybrid power welding robot system's performance. The experimental findings demonstrate that using the optimization technique in this study, the durability of FC power output is increased by 11.26%, and hydrogen consumption is lowered by 3.24%.

The experimental findings demonstrate that the energy optimization technique not only ensures high precision and real-time performance of the welding robot system but also improves the hybrid welding robot system's stability and energy economy while lowering energy usage.

### 3.5. Support Vector Machine

Support vector machines (SVMs) are also excellent choices for high-dimensional regression analysis and are applicable in real applications. Vapnik and colleagues developed the SVM technique for pattern recognition. SVMs offer remarkable generalization power compared to ANNs, and support vector regression is one of the most used implementations for regression and function prediction. The SVM regression approach employs the structural risk minimization (SRM) rule instead of the empirical risk minimization (ERM) criterion used by most ANNs.

SVM has been effectively used as an ML technique for classification and regression problems. Although it was designed for linear classification, now it has been extended to nonlinear issues. It uses kernel functions to turn the data into a high-dimensional feature space for nonlinear classification, then looks for the hyperplane with the maximum distance to each type of observation. It has performed exceptionally well in binary and multiple classification tests.

A Kheirandish et al. used a support vector machine (SVM) to forecast the performance of a PEMFC system in a commercially available electronic bicycle [112]. The key benefit of the study's findings is that they make it easier to utilize carbon-free fuels instead of carbon-based ones, which reduces energy consumption. SVMs, which are excellent tools for forecasting PEMFC performance, are employed since such cells are nonlinear, multivariable systems that are challenging to describe using standard approaches. Experimental data from a 250 W PEMFC were used to estimate parameters for the V–I, P–I, and efficiency–power curves, and the data were then used to forecast total PEMFC performance. This technique was compared to a multi-layer perceptron (MLP) artificial neural network model to assess the functioning of the recommended model. It has been shown that the inaccuracy of the SVM model is substantially less than that of the MLP model and that the suggested technique performs better in predicting the PEM FC curve for the electric bicycle. It was discovered that the SVM prediction model for the power–current curve has a coefficient of determination of approximately 99%, compared to 97% for the MLP model, making the proposed black box SVM PEMFC model suitable for monitoring and simulating FC performance in the electric bicycle, which is advantageous for its variety of energy-saving applications.

Because of their great efficiency and environmental safety, polymer electrolyte membrane FCs are being investigated as a viable source of power generation. X. Peng and colleagues examined the relationship between power density and operational factors such as operating temperature, FC pressure, anode relative humidity, cathode relative humidity, porosity of gas diffusion electrode (GDE), and GDE conductivity [113]. However, identifying the operating parameters that will enhance the power density of PEMFCs has received little attention. Based on the AI method of support vector machines, the current work offers the best design of a power density model for PEMFCs (SVM). The experimental data and the proposed power density model correspond well. After that, a simulation profiler is created to ensure that it is unaffected by changes in operating circumstances, and conclusions about correlations between power density and operational parameters are studied. The findings demonstrate that the FC pressure and GDE conductivity are the two most important inputs in the proper operation of a PEMFC. The operating temperature of 86.2 K, the FC pressure of 3.44 atm, the relative humidity of the anode of 50%, the relative humidity of the cathode of 64.4 percent, the porosity of GDE of 0.5, and the conductivity of GDE of 997.7 S/m give a greater power density value of 870 mW/cm<sup>2</sup> to PEMFCs, according to the formulated model.

Using a support vector machine, ZD Zhong and co-authors reported on a modeling investigation of PEMFC performance (SVM) [114]. A PEMFC is a multivariable, nonlinear system that is difficult to model using traditional approaches. In terms of generalization, the SVM is superior, and this capability is independent of the dimensionality of the input data. These two advantages combine to make it an effective tool for predicting how a PEMFC would perform under various operating situations. A PEMFC system SVM model is created, optimized, and evaluated in this paper. After determining the model using chosen experimental data, it is utilized to predict PEMFC performance. It is demonstrated that the model can generate a prediction in 10 milliseconds with a squared correlation value of 99.7%. As a result, the suggested black-box SVM PEMFC model may be used to simulate, control, and monitor the functioning of an FC in real-time.

Using a least-squares support vector machine (LS-SVM), HB Huo et al. presented a nonlinear modeling investigation of a solid oxide FC (SOFC) stack [115]. The SOFC is a nonlinear, multi-input, multi-output system that is difficult to model using conventional methods. Most available models are now based on conversion rules, which are quite beneficial for cell design. They are, however, far too sophisticated to be used in the design of control systems. This study attempts to eliminate internal complications and proposes a black-box model of the SOFC based on LS-SVM in order to assist in the creation of a valid control strategy. The simulation experiments show that the model can be established using LS-SVM. Simultaneously, experimental comparisons of the LS-SVM model and the radial basis function neural network (RBFNN) model show that the LS-SVM outperforms the RBFNN in forecasting stack voltage with various fuel utilizations. Furthermore, viable control strategy studies such as predictive control and robust control may be established using this black-box LS-SVM model.

In SOFC functioning, cell temperature management is critical. Y.W. Kang et al. present a dynamic temperature model of an SOFC utilizing least squares support vector machines (LS-SVMs) in order to build effective temperature management techniques using model-based control approaches [116]. A nonlinear autoregressive with exogenous inputs (NARXs) model is used to characterize the SOFC's nonlinear temperature dynamics, which is achieved using an LS-SVM regression model. Variable selection, training set generation, and LS-SVM parameter optimization are all covered in-depth as part of the development of the LS-SVM temperature model. Extensive validation studies show that the proposed LS-SVM model is effective enough to be employed independently of the SOFC process, simulating its temperature response using simply process input data across a large working range. Apart from the modeling method itself, the LS-SVM temperature model benefits from the approaches of automatically building the training set and tweaking hyperparameters via GA. The suggested LS-SVM temperature model may be used to create temperature management strategies for SOFCs with ease.

### 3.6. Extreme Learning Machine

The ELM model is one of the most intriguing networks. This network generates a consistent pattern with a wide range of feature transmissions that are used in the hidden layer, which is directly used in multi-category classification and regression. The ELM is a learning technique for Single Hidden Neural Networks (SHNN) that enables random bias and input weight initialization as well as for analytic output weight evaluation. As a result, this approach allows the network to be trained in a matter of minutes [117].

For optimal control and behavior analysis, a precise, rapid, and robust parameter extraction technique for SOFC models is critical. To extract unknown characteristics of solid oxide fuel cell models, including electrochemical models and simple electrochemical models, a unique extreme learning machine-based method is proposed by Yang and colleagues [118]. An extreme learning machine is initially used to handle two difficult challenges (e.g., data scarcity and noised data) by anticipating extra data and updating noised data. The raw data from a 5-kW solid oxide fuel cell stack, as well as processed data, are then transferred to successfully guide eight renowned meta-heuristic algorithms for

optimal parameter extraction. A detailed comparison based on varied training data is used to properly analyze the performance of an extreme learning machine under two typical operation settings. The simulation results demonstrate that the suggested approach may effectively contribute to the search for efficient model parameters while maintaining high accuracy, conspicuous stability, fast speed, and great robustness. The accuracy of parameter extraction for electrochemical models and basic electrochemical models, in particular, can be enhanced by up to 49.3% and 65.6%, respectively.

The prognostics of proton exchange membrane fuel cell (PEMFC) deterioration can be used to develop an appropriate maintenance plan to enhance its lifetime and performance. Chen et al. proposed the voltage deterioration for PEMFC under various situations forecasted by utilizing a novel prognostics method based on GA and ELM [101]. The unique prognostics method takes into account the impacts of PEMFC load current, relative humidity, hydrogen pressure, and temperature on PEMFC degradation. The ELM first creates the voltage degradation prediction model for PEMFC. The GA is then used to select the best parameter for the proposed degradation prediction model. Moreover, the suggested prognostics method's voltage degradation prediction is validated using data collected from the PEMFC in a real postal fuel cell electric vehicle (PFCEV) in real settings and PEMFC at dynamic load current. The experimental results show that the suggested prognostics method can estimate voltage deterioration for PEMFC in PFCEV under real-world conditions. The suggested method outperforms existing traditional data-based prognostics methods for PEMFC voltage deterioration prediction at dynamic load current.

A novel, deep learning-based methodology for optimal and efficient modeling of proton-exchange membrane fuel cells was proposed by Han and Ghadimi [119]. A hybrid technique based on CNN and ELM networks is used to do this. The model is refined to achieve the best outcomes using a new, improved metaheuristic known as the Improved Honey Badger Algorithm (IHBA). The upgraded version of the IHBA is used to increase the accuracy of the model findings and to give fast convergence for the method. The designed model is then applied to a model to validate its efficacy. The findings show that the suggested model is consistent with experimental training data, with a maximum error rate of 0.039. The suggested model's findings are then compared to a CNN-based model estimator to validate its better efficiency. Although both model estimators have acceptable confirmation with the experimental data, the suggested model delivers more satisfactory findings with a lower error value.

#### 4. Summary and Outlook for Future

In summary, this review gives a clear picture of the various types of FCs, such as PEMFC, AFC, DMFC, PAFC, MCFC, and SOFC. Additionally, common types of AI—viz., genetic algorithm, particle swarm optimization, random forest, support vector machine, artificial neural network, and Extreme Learning Machine—used in FC technology are described.

In the case of the application of ANN in the FC,

- The computational models of transport events inside a solid oxide FC anode were examined.
- The grey wolf optimizer is utilized, which has rapid, sturdy, and simple properties.
- A novel optimization method for automatically collecting characteristics from the impedance spectra of polymer electrolyte membrane FCs was observed.
- A neural network method used to determine the voltage and current of a PEMFC was summarized.
- A technique to improve the performance and durability of an FC by predicting the local current distribution was also discussed.

In the GA section,

- The energy management strategy for an FC hybrid electric vehicle with an FC as the primary power source and a battery as a backup power source was illustrated.

- A GA-based optimized rule-based EMS for optimal power allocation between the FC and the battery system was explored.
- An effective method for controlling the flow channel design of the bipolar plate (BPP) was devised to obtain the greatest performance of PEMFCs.
- GA was used to improve a high-temperature PEMFC's flow channel.
- The voltage degradation for PEMFC under various conditions is projected using a new prognostics approach based on GA, and an extreme learning machine (ELM) was explained.

In order to understand the role of PSO in FC,

- A novel grey neural network model (GNNM) strategy in which GNNM is combined with particle swarm optimization (PSO) and the moving window method to predict PEMFC degradation under various operating conditions was described.
- For optimal parameter estimations, chaos-embedded particle swarm optimization was used to model polymer electrolyte membrane FCs.
- The comparison and contrast of two Maximum Power Point Tracking (MPPT) strategies, one based on the Mamdani Fuzzy Inference System and the other on the PSO algorithm, to keep the output power of an FC stack extraordinarily near to its peak was discussed.
- An optimization approach for scaling the modules of a PEMFC-battery hybrid energy system (HES) to provide the required driving force for passenger trains was illustrated.
- A simplified form of the competitive swarm optimizer (SCSO) was introduced to deal with the parameter identification challenge of SOFC models. The flow channel of a high-temperature PEMFC was optimized using GA.

The implication of RF in FCs was analyzed.

- An improved PCA approach was employed to create the essential features of RF and Support Vector Regression to evaluate two efficient ML algorithms.
- An ensemble model based on a stacked extended short-term memory model that integrates three machine-learning models, including long short-term memory with attention mechanism, support vector regression, and random forest regression, to improve the deterioration prediction of a PEMFC stack was explained.
- A detailed performance evaluation and a random forest prediction technique to examine system energy optimization in order to improve the stability, real-time performance, and economy of the PEMFC hybrid welding robot system were carried out.

The SVM tool in FC is described

- To predict the performance of a PEMFC system in a widely available electronic bicycle using SVM.
- The link between power density and operational parameters such as operating temperature, FC pressure, anode relative humidity, cathode relative humidity, GDE porosity, and GDE conductivity was established using SVM modeling analysis of PEMFC performance. The optimum design of a power density model for PEMFCs was also performed with SVM.
- A nonlinear modeling investigation of an SOFC stack using a least-squares support vector machine was illustrated.
- A dynamic temperature model of an SOFC using least-squares support vector machines in order to build effective temperature management techniques using model-based control approaches has also been portrayed.

The ELM an advanced AI tool was used to

- Extract unknown characteristics of solid oxide fuel cell models, including electrochemical models and simple electrochemical models.
- Forecast a novel prognostics method based on GA and ELM for the voltage deterioration in PEMFC under various situations.

- Optimal and efficient modeling of proton-exchange membrane fuel cells using a hybrid technique based on CNN and ELM networks.

Among all the methods discussed above, ANN is considered to be a better AI tool suitable for studying the performance of FCs. ANN is a cost-effective and rapid technique that is a subset of machine learning. It was observed that both classic computing methods and innovative approaches based on AI techniques had been shown to achieve equivalent accuracy in FC modeling. The model used to estimate the performance of the FC is quite accurate. FC technology has excellent performance qualities, particularly in terms of efficiency, and can contribute to the overall effort to improve power generation. AI, notably artificial neural networks, can be trained to accurately imitate the functioning of an FC. AI is a strong tool for FC design, simulation, control, and optimization. The capacity of AI-based and data-driven modeling to find the conditions necessary for optimal power output is considerable. The benefits of AI-enabled technologies include the ability to forecast FC disadvantages during unexpected demand increases and variable energy output. AI can assist in identifying trends that are difficult to detect through trials and can examine a vast number of situations in a cost-effective manner. It is worth noting that AI approaches are susceptible to dataset quantity and noise, which might impair model development time and accuracy.

Model verification for ML-based defect diagnosis is still in progress, with test data being used to assess the model's efficacy. Integration problems, such as restricted computing capability and temporal delay, have not yet been examined. If feasible, fault diagnosis tries to raise the recognition rate to 100%. On the other hand, a single diagnostic model can only achieve a restricted recognition capacity, which may be insufficient for the real application. FCs may be taught and programmed to regulate internal functioning and flow rates to improve performance from a strategic standpoint and with adequate data available. The usage of optimization approaches should be explored in future AI applications in HRESs. The use of hybrid optimization methods, which integrate two or more optimization approaches, has been proven to save computing time. Future research should also compare the viability of HRES with other FCs and address and provide answers to difficulties like data integrity in AI and the complex nature of AI algorithms.

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