Modeling and Optimization of Proton Exchange Membrane Fuel Cell Performance Using Artificial Neural Networks and Metaheuristic Algorithms

Thesis submitted by

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Statement of Originality

I, Sankhadeep Ghosh, registered on the 11th of June, 2018 do hereby declare that this thesis entitled "Modeling and Optimization of Proton Exchange Membrane Fuel Cell Performance Using Artificial Neural Networks and Metaheuristic Algorithms" contains a literature survey and original research work done by the undersigned candidate as part of Doctoral studies.

All information in this thesis has been obtained and presented in accordance with existing academic rules and ethical conduct. I declare that, as required by these rules and conduct, I have fully cited and referred all materials and results that are not original to this work.

I also declare that I have checked this thesis as per the "Policy on Anti Plagiarism, Jadavpur University, 2019", and the level of similarity as checked by iThenticate software is 8%.

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This is to certify that the thesis entitled "Modeling and Optimization of Proton Exchange Membrane Fuel Cell Performance Using Artificial Neural Networks and Metaheuristic Algorithms" submitted by Mr. Sankhadeep Ghosh, who got his name registered on 11^{th} of June, 2018 for the award of Ph.D. (Engg.) degree of Jadavpur University, is absolutely based upon his own work under the supervision of Dr. Mehabub Rahaman and Dr. Avijit Ghosh and neither his thesis nor any part ofthe thesis has been submitted for any degree/diploma or any other academic award anywhere before.

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Dedicated to my son

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Date: 07/03/2025 **Sankhadeep Ghosh**

Abstract

Proton exchange membrane fuel cells (PEMFCs) are a challenging energy conversion technology used in transportation and distributed power generation due to their advantageous characteristics, including high power density, low operating temperature, minimal emissions, negligible noise, and high efficiency. Designing a (PEMFC) fuel cell model is exceedingly challenging because of its multivariate in nature. All the input variables in PEMFC are changing under dynamic operating condition. Therefore, it is very difficult to get steady power output from PEMFC under simulated environment due the complex thermodynamics which governed by the Nernst equation. The optimization of various input parameters including in the governing equations of PEMFC is much essential to achieve best performance for multi-input multi-output system. Mostly the data driven techniques are used to predict the real time voltage and power losses with respect to the input parameters in PEMFC.

It has been observed that the various mathematical techniques are used for the optimization of PEMFC including fuzzy logic, Artificial Neural network (ANN), or adaption of metaheuristic algorithm etc. In case of optimization using ANN, the most important input parameters like stack temperature, pressure, relative humidity, partial pressure of hydrogen, partition pressure of oxygen, anode stoichiometry, and cathode stoichiometry have been considered to analyze the fuel cell performance. These parameters are given as input layer of ANN, which passes through hidden layer. The ANN model utilized the Levenberg-Marquardt (LM) learning technique to develop a multilayer perceptron network, demonstrating that the LM back-propagation algorithm is the most effective method for determining fuel cell performance parameters where the predicted voltage of a single cell was 0.8 volt.

The developed ANN model reveals both the maximum and minimum power outputs and the optimal operating conditions for any load changes, which helps to predict the best PEMFC

operating conditions for achieving maximum power output. An R^2 (coefficient of determination) value of 0.98 indicates that the ANN model has an excellent fit and can accurately predict the actual output voltage with 98% precision. It is observed that the best ANN outputs results are due to the approximation of the various parameters in the hidden layer.

The predicted output voltage from the ANN model is equal to the open-circuit voltage of the fuel cell minus the voltage corresponding to the loss components of the fuel cell. These losses are categorized as activation losses, Ohmic losses and concentration losses. By minimizing these losses, the predicted output voltage can be increased, resulting in higher stack power generation. Each loss is governed by some parametric co-efficient (for example membrane resistance, contact resistance etc.). These co-efficient values are not specific. To minimize the loss voltages, these co-efficient plays an important role. Based on this concept, a metaheuristic algorithm has been introduced to optimize these coefficients, effectively reducing loss voltages, achieving the actual output voltage, and ultimately increasing power generation. During this phenomenon of reducing losses, it was tried to evaluate the parametric co-efficient in such a manner that the loss voltage can be controlled to minimum value using metaheuristic Algorithm.

By coupling an ANN model with a metaheuristic optimization algorithm, the methodology allows predicting the overall voltage, systematically minimizing the contributions from concentration, activation, and ohmic losses, and enhancing the net voltage output and overall power efficiency of the PEM fuel cell. This hybrid approach leverages the ANN's ability to model complex nonlinear relationships and the metaheuristic's strength in handling multivariate optimization problems, ultimately leading to improved fuel cell performance through reduced internal losses.

In this research, it has been analyzed that several metaheuristic algorithms, each operating based on a unique mechanism. For example, the Artificial Bee Colony (ABC) algorithm is inspired by the foraging behaviours of bees, while the Genetic Algorithm (GA) mimics biological evolution. This research focuses on determining the parametric coefficients under different optimization algorithms and tabulating these values, which ultimately lead to the "calculated voltage" of a Proton Exchange Membrane Fuel Cell (PEMFC). The Sum of Squared Errors (SSE), introduced earlier, quantifies this difference. The primary objective to introduce metaheuristic algorithm along with ANN is to minimize the SSE. It can be observed that the around 20% improvement in the open circuit voltage due to the incorporation of Dynamic Ant Colony Optimization (DACO) in the metaheuristic algorithm. This improvement can be attributed due to the minimization of various losses when used DACO over Ant Colony Optimization (ACO).

The Ant Colony Optimization (ACO) is a widely used optimization technique inspired by the natural path-selection behaviour of ants searching for food, where the most efficient route is reinforced and selected. However, in conventional ACO, the food particles remain stationary over time. To address this limitation, a novel optimization technique called Dynamic Ant Colony Optimization (DACO) was proposed. Unlike ACO, DACO considers food particles as dynamic entities, increasing accessibility and improving accuracy. DACO has been tested using ten different benchmark functions and compared against other optimization algorithms, including GA, ABC, ACO, and GWCO. The results demonstrate that DACO is a more reliable algorithm for minimizing SSE. Its dynamic nature allows for a lower SSE with the same or lesser computation time while maintaining efficiency across multiple domains. Additionally, DACO exhibits superior convergence and provides more accurate results than other algorithms such as DE, ABC, ACO, and GWCO. Although DACO proves to be an effective metaheuristic algorithm for the minimization of various characteristic losses of the OCV, further an enhanced technique known as Wild Chimpanzee Hunting Optimization Algorithm (WCHO) was developed to get higher OCV. This algorithm follows a similar working principle to DACO but incorporates additional features such as time of flight and range of oscillation to refine results. The convergence curve indicates that WCHO achieves a lower SSE than DACO, albeit at the cost of increased computational time.

Applying WCHO to the fuel cell output equation produces parametric coefficients closely aligned with those obtained from DACO. However, WCHO requires a longer computation time. Ultimately, while WCHO offers sharper results, DACO remains the preferred metaheuristic algorithm for the objective function due to its faster convergence time approx. 30% less.

Henceforth this optimization algorithm also used in Optimization of PID controller. This article discusses improving the performance of PEMFCs by controlling a DC/DC converter using various methods, including conventional PID, DACO (Dynamic Ant Colony Optimization)-based PID, DACO-based FOPID, PSO-based PID, PSO-based FOPID, BEE Colony-based PID, and BEE Colony-based FOPID controllers. A Simulink model of a PEMFC was created with controllers and dual inputs for oxygen airflow and hydrogen flow. The suggested methods were compared with the system-generated results and a conventional PID controller. The optimization algorithms DACO, BEE Colony, and PSO were used with fitness functions IAE, ISTE, and ITAE. Performance was evaluated based on rising time (T_S), maximum overshoot (M_P%), and fitness function value. The suggested techniques optimized the PID and FOPID parameters, and outcomes were analysed against conventional PID methods, identifying the optimal values empirically. The research found that the proposed methods were more effective than the normal PID method, with the DACO-FOPID approach being the most superior. Simulation results indicated that control performance was acceptable for a PEMFC model using traditional PID and FOPID controllers adjusted by DACO, BEE colony.

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Terminology Used

μ = viscosity (Pas^{-1})

ρ = density (kgm^{-3})

P = pressure (atm)

η = overpotential (V) or efficiency

$\vec{u}$ = velocity (ms^{-1})

σ = conductivity (Sm^{-1})

K = permeability (m^2)

γ = concentration exponent

R = universal gas constant ($8.314 Jmol^{-1}K^{-1}$)

c_p = constant − pressure heat capacity ($Jkg^{-1}k^{-1}$)

α = transfer coefficient

k = thermal conductivity ($Wm^{-1}k^{-1}$)

ϕ = phase potential

ζ = stoichiometric ratio

T = temperature (C)

R_{ohm} = ohmic resistance (Ω)

F = Faraday's constant ($96485 Cmol^{-1}$)

List of Abbreviations

- **PEMFC** - Proton Exchange Membrane Fuel Cell
- **IC** - Internal Combustion
- **PEM** - Proton Exchange Membrane
- **SOFC** - Solid Oxide Fuel Cell
- **AFC** - Alkaline Fuel Cell
- **MEA** - Membrane Electrode Assembly
- **MPL** - Microporous Layer
- **GDL** - Gas Diffusion Layer
- **CL** - Catalyst Layer
- **CIAD** - Computer Intelligence-Aided Design
- **AI** - Artificial Intelligence
- **ANN** - Artificial Neural Network
- **MOO** - Multi-Objective Optimization
- **LM** - Levenberg-Marquardt
- **PSO** - Particle Swarm Optimization
- **ABC** - Artificial Bee Colony
- **ACO** - Ant Colony Optimization
- **GWO** - Grey Wolf Optimization
- **PEMFC** - Proton Exchange Membrane Fuel Cell
- **MEA** - Membrane Electrode Assembly
- **MPL** - Microporous Layer
- **GDL** - Gas Diffusion Layer
- **CL** - Catalyst Layer

- **SOFC** - Solid Oxide Fuel Cell
- **AFC** - Alkaline Fuel Cell
- **PFSA** - Perfluoro Sulfonic Acid
- **ANN** - Artificial Neural Network
- **FLC** - Fuzzy Logic Controller
- **NNT** - Neural Network Training
- **RNN** - Recurrent Neural Network
- **CNN** - Convolutional Neural Network
- **PSO** - Particle Swarm Optimization
- **ACO** - Ant Colony Optimization
- **BCO** - Bee Colony Optimization
- **SFLA** - Shuffled Frog-Leaping Algorithm
- **DHOA** - Deer Hunting Optimization Algorithm
- **MPC** - Model Predictive Control
- **MOO** - Multi-Objective Optimization
- **CFD -** Computational Fluid Dynamics
- **PEMFC**: Proton Exchange Membrane Fuel Cell
- **PID**: Proportional-Integral-Derivative
- **FOPID**: Fractional-Order Proportional-Integral-Derivative
- **DACO**: Dynamic Ant Colony Optimization
- **PSO**: Particle Swarm Optimization
- **ABC**: Artificial Bee Colony
- **ANN**: Artificial Neural Network
- **IAE**: Integral of Absolute Error

- **ITAE**: Integral of Time Absolute Error
- **ISTE**: Integral of Square Time Error
- **PH_2**: Partial Pressure of Hydrogen
- **PO_2**: Partial Pressure of Oxygen
- **RH_a**: Relative Humidity of Anode
- **RH_c**: Relative Humidity of Cathode
- **T**: Stack Temperature
- **nC**: Number of Cells
- **VFC**: Fuel Cell Voltage
- **EC**: Open Circuit Voltage of a Single Cell
- **F**: Faraday Constant
- **R**: Universal Gas Constant
- **A**: Area
- **K**: Kelvin (Temperature)
- **ACO**: Ant Colony Optimization
- **GWOCS**: Grey Wolf Optimizer Coupled with Crow Search
- **LM**: Levenberg-Marquardt
- **WCHO**: Wild Chimpanzee Hunting Optimization

CHAPTER 1

Introduction

1.1 Introduction to proton exchange membrane fuel cell (PEMFC)

The interest in the development of alternative energy generation devices is growing rapidly to overcome the challenges of global warming and environmental pollution due to the use of fossil fuels. Internal combustion (IC) engine enhances the generation of CO and CO_2 (Ghosh et al., 2013). To replace traditional fossil fuels and internal combustion engines, this has raised the demand for clean, renewable energy sources as well as alternative energy-producing technology due to its great thermodynamic efficiency and nearly negligible emissions. Hydrogen is utilized as the fuel, and oxygen is used as the oxidant. Therefore, fuel cells have drawn the attention of researchers and scientists as a potential replacement for internal combustion engines (Alzubaidi et al., 2021).

Fuel cells generate electricity through the chemical reaction between a fuel (usually hydrogen) and an oxidant (usually oxygen or air). Unlike conventional engines, they don't burn fuel but instead undergo an electrochemical process that combines the hydrogen and oxygen to produce electricity, water, and heat (Askarzadeh et al., 2010). The hydrogen gas enters the fuel cell at the anode, where it is split into electrons and protons then the protons pass through the electrolyte to the cathode where oxygen gas enters and combines with the electrons (which travel through an external circuit to generate electricity) and the protons to form water (Hochreiter et al., 1997).

The main types of fuel cells include, proton exchange membrane fuel cells (PEMFC), which are ideal for vehicles, stationary, and portable power generation (Watts to Kilowatts power output ranges) due to their quick start, low temperature operation, solid structure, and lightweight design. On the other-hand, solid oxide fuel cells (SOFC) are suitable for kilowatts to megawatts power generation, with high efficiency and the ability to use a variety of fuels

(Goodfellow et al., 2016). However, SOFC operates at very high temperature which is the main drawback as compared to PEMFC.

It can be noted that the fuel cells are most commonly used for being a clean energy generation device as compared to IC engine with water being the primary by product, which makes them environment friendly.

In this regard, the proton exchange membrane fuel cells (PEMFC) have received a lot of research interest because they can run in low temperatures and utilization of hydrogen was done very effective (Michelucci et al., 2022). PEMFC is considered to be an efficient electrochemical energy conversion technology that can convert hydrogen's chemical energy into electrical and thermal energy without burning it or releasing any air pollutants (Liyun et al., 2024). PEMFCs are adaptable and have a variety of uses, including as vehicle power sources because of their high-power density, quick start-up, low operating temperature, and mobility. The two most essential parts of a typical single PEMFC unit are the bipolar/end plates (BPs) and the membrane electrode assembly (MEA), which is shown in figure 1.1 The proton exchange membrane (PEM) is located in the centre of the MEA. This structure consists of microporous layers (MPLs), gas diffusion layers (GDLs), and catalyst layers (CLs) on the anode and cathode sides, respectively. PEMs function as the medium for ion conductance between the anode and cathode in a fuel cell, while also acting as a barrier to prevent the mixing of fuels and oxidants apart from acting as electron insulator. The oxidation and reduction reaction reactions take place at anode and cathode catalytic sites, respectively. The MPL and GDL are deployed ensuring that catalysts are uniformly distributed and enable the circulation of fuel and oxidants. The additional critical auxiliaries components of fuel stack including bipolar plate, MEA, catalyst layers, and coolant flow channels are shown in the enlarge view of figure 1.1.

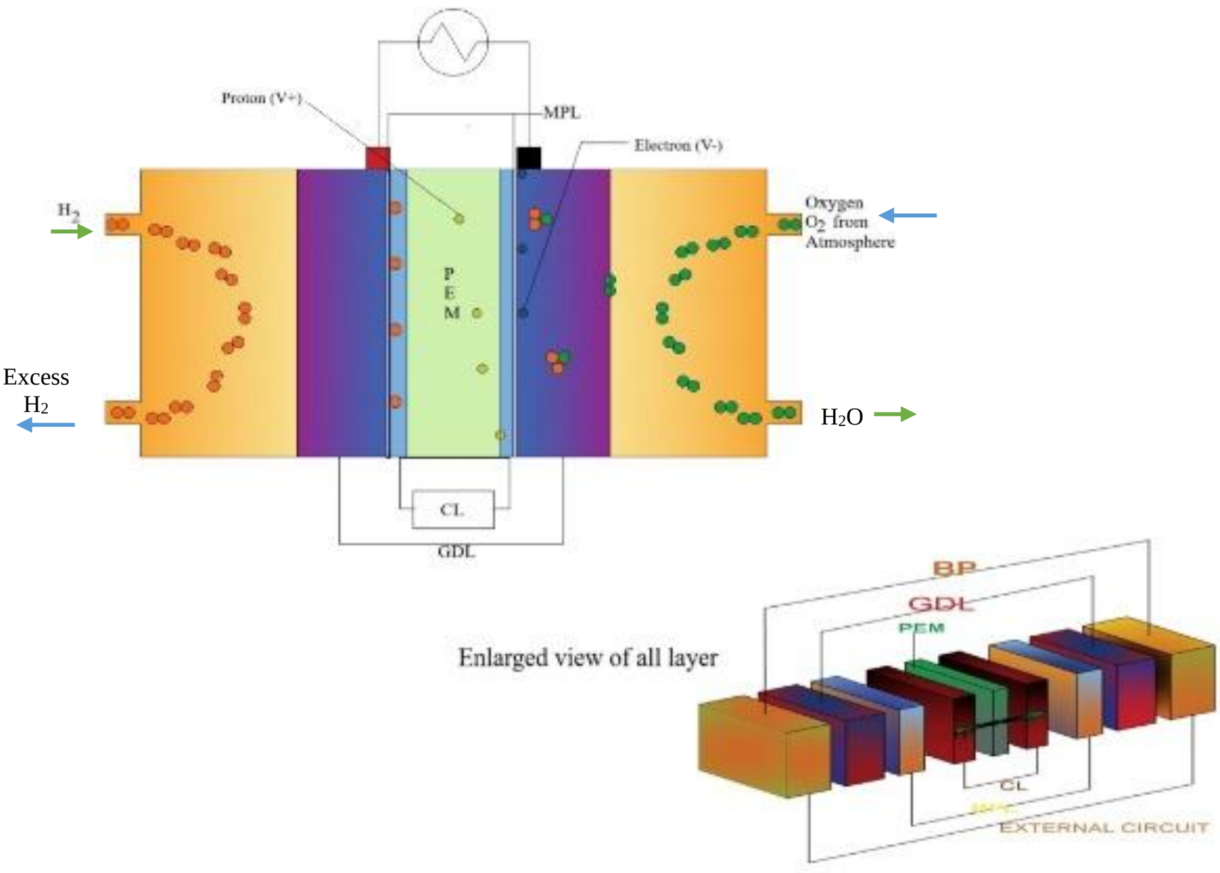

Figure 1.1 Cross-section and expanded view of PEMFC and the transportation of the electron, proton, and gases (Ghosh et al., 2024)

1.1.1 Working phenomenon of PEMFC

In the PEMFC, the proton conducting membrane is used to act as the electrolyte apart from the separating O_2 and H_2 and transport only proton from anode to cathode. The hydrogen oxidation and oxygen reduction reaction are established at the anode and cathode, respectively (Ghosh et al., 2012).

$$Anode \rightarrow 2H_2 \rightarrow 4H^+ + \{4e^-\} \quad [1]$$

Water is generated as a by-product due to the reaction between oxygen and hydrogen ions in presence of electron at the cathode. The cathodic reduction reaction and over all reaction are mentioned as below:

$$Cathode \rightarrow O_2 + \{4e^-\} + \{4H^+\} \rightarrow 2H_2O \quad [2]$$

$$Overall \rightarrow H_2 + \frac{1}{2}O_2 \rightarrow H_2O \quad [3]$$

Operating factors such as stack temperature, hydrogen and oxygen partial pressure, humidity, hydrogen and oxygen mass flow rate, and load change are the key determinants of a PEMFC's output voltage (Mnih et al., 2015). The polarization curve mostly illustrates a fuel cell's static properties. As the reduction reaction current density rises, the output voltage drops nonlinearly. For the configuration to function at its best, effective and trustworthy operational methods or systems are also required in addition to the PEMFC stack. Internal-section view and expanded view of PEMFC and transportation of the electron, proton, and gases is displayed in figure 1.1. The complicated fuel cell systems were composed of a variety of interconnected subsystems, such as a monitoring system, a controlling system, and another multifunctional system (Ghosh et al., 2012). A fuel cell cannot operate effectively on its own; it requires the collaboration of numerous subsystems. The fuel cell's operating status is monitored by the monitoring system. The reactant system, temperature management systems, and water management systems form the control system, which can set parameters immediately in response to demand (Kahia et al., 2023) . The PEMFC application in the various field also discusses in the subsequent section.

1.1.2 Application of PEMFC

PEMFC is used in a wide range of applications, including hybrid electric vehicles, portable power sources, home power plants, and automobiles. PEMFCs are required to function effectively in several demanding contexts. Over the past two decades, PEMFC technology has evolved fast. However, several problems are impeding the commercialization of PEMFC (Eberhart et al., 1995). The PEMFC stack's technical issues, including MEA preparation, water and temperature control, flow channel design, etc., must also be handled in addition to the challenges connected with storing and transporting hydrogen. In addition, PEMFC is being designed and implemented using computer intelligence-aided design (CIAD) to reduce costs, increase power density, and improve durability, surpassing existing technologies (Ghosh et al., 2013). Precision and effectiveness have increased, and challenging issues that were hard to tackle manually have been resolved. The PEMFC industry is increasingly utilizing AI techniques like deep learning, fuzzy logic, and neural networks, with a significant focus on fuzzy logic in the electric vehicle control system (Barbir et al., 2006). Heuristic algorithms are the most often used ANN for the multi-objective optimization (MOO) technique. In this context the optimizing of output of PEMFC is being described. Several methods are used to check and reach the best possible outcome of PEMFC which is firstly using of Artificial Neural Network in development of configuration of PEMFC and secondly use of different optimization algorithm to achieve the optimum output from PEMFC by modelling and optimization (Bengio et al., 2015). This will help to design a best control strategy for the effective application of PEMFC in the real time operation. The optimization on PEMFC using various methods are discussed below.

1.2 Optimization of PEMFC using different technique

Before going deep into the further discussion let get familiar with some commonly used modelling concept and their application in the PEMFC.

1.2.1 Concept of fuzzy logic

Fuzzy logic is a fascinating concept that extends beyond the traditional binary logic used in classical computing. It deals with reasoning that is approximate rather than fixed and exact. It works on Fuzzy Sets in which instead of dealing with absolute true or false values, fuzzy logic operates on degrees of truth (Dietterich et al., 2000). Then Membership Functions are curves that define how each point in the input space is mapped to a membership value (between 0 and 1). Different membership functions (e.g., triangular, trapezoidal, Gaussian) can be used to define fuzzy sets. Fuzzy logic systems use a set of if-then rules followed by inference in PEMFC optimization combines the rules and dataset to make decisions based on the degrees of truth (Srivastava et al., 2014).

1.2.2 Optimization using Artificial Neural Network (ANN) in PEMFC

Artificial Neural Networks (ANNs) are computational models inspired by the human brain. They consist of interconnected units called neurons, which process and transmit information through weighted connections. The main structure of ANN comprises of neurons and layers where former is similar to biological neuron which receive inputs, process them and generates output, and later is further consist of input layers, intermediate layers and output layers and each layers is iterative as input layer receives initial data, and all the actual processing and transformation of data take place, and this layer may be vary as per objective, then output layer produces the final output, such as classification or prediction. In this case of optimization of PEMFC the Levenberg-Marquardt learning technique (Eberhart et al., 1995) was used to create the multilayer perception network which is further discussed in chapter 3. It is evident that the best learning technique for determining the fuel cell performance parameters is the Levenberg Marquardt (LM) back-propagation algorithm. It can be seen that the projected values from the given neural network can be used to estimate the PEM fuel cell's (PEMFC) performance in different application (Dorigo et al., 2004).

1.2.3 Optimization using metaheuristic algorithm in PEMFC

Metaheuristic algorithms are advanced optimization techniques designed to find good solutions for complex problems where traditional methods might struggle and search space is very large. They are called "metaheuristic" because they combine different rules and strategies to explore the search space efficiently (Eusuff et al., 2003).

Metaheuristics are algorithms that use heuristics to guide search for solutions, often incorporating randomness to avoid local optima. Inspired by natural phenomena, they aim to explore the entire search space for near-optimal solutions (Tsai et al., 2023).

1.2.3.1 Particle Swarn Optimization in PEMFC

The social behaviour of fish schools or flocks of birds served as the inspiration for the potent metaheuristic algorithm known as particle swarm optimization (PSO). PSO, which was created in 1995 by Dr. Eberhart and Kennedy, simulates a population of potential solutions, or particles, moving through the search space in order to solve complicated optimization problems (Martins et al., 2021). To use this optimization technique, it has to conform to certain guidelines. The search space is initialized with a population of particles representing possible solutions, each with a velocity vector, and key parameters controlling exploration and exploitation balance. Then the objective function is used to evaluate the fitness of each particle's position, assessing the quality of the solution represented by the particle's position followed with the objective function which is used to evaluate the fitness of each particle's position, assessing the quality of the solution represented by the particle's position (Barbir et al., 2012).

In many research work PSO is used to choose the best fitted value for different parametric constant in the formula of output voltage of PEMFC and the results were significantly admirable in this research a novel optimization technique call dynamic ant colony optimization is used to find the best optimized values of those parametric constant and compared it with existing results of that from PSO algorithm, the implementation of PSO for comparison of this research work is further discussed in chapter 4 and chapter 5 (Ma et al., 2024).

1.2.3.2 Artificial Bee Colony Optimization in PEMFC

The Artificial Bee Colony (ABC) algorithm is a metaheuristic optimization technique inspired by the foraging behaviour of honey bees. It was developed in 2005 (Karaboga et al., 2005) and is particularly effective for solving numerical optimization problems. This ABC algorithm is standing on few parameters those are food sources which represent potential solutions to the optimization problem. It can be noted that the Bees represent the parameter that search for solution which is nothing but food sources (Mo et al., 2023).

The ABC algorithm is a flexible tool for a range of optimization tasks because of its simplicity and capacity to strike a balance between exploration and exploitation (Liao et al., 2024). The established ABC fitness function algorithm is used to compare with the developed Dynamic Ant Colony algorithm which is discussed in chapter 4.

1.2.3.3 Ant Colony Optimization in PEMFC

Ant Colony Optimization (ACO) is a metaheuristic algorithm developed by Marco Dorigo in the early 1990s, inspired by ants' foraging behaviour. It is effective for solving combinatorial optimization problems and is a probabilistic technique for finding good paths through graphs. The algorithm mimics ants' collective intelligence in finding efficient food paths, with each ant constructing its own route based on factors like node degree (δ(v)), attractiveness function (η_{ij}), trail level (τ_{ij}), and food probability (Wu et al., 2020).

The moving probability formula for ant k is:

$$P_{ij}^{k} = \frac{\left(\tau_{ij}\right)^{\alpha} * \left(\eta_{ij}\right)^{\beta} * \exists * \left(\delta_{\ ij}\right)}{\sum_{k=0}^{m} h \in allowedj(\tau_{ih})^{\alpha} * (\eta_{ih})^{\beta} * \exists * (\delta_{\ ih})} \qquad [4]$$

where mm is the maximum number of distinct paths, αα regulates the influence of the pheromone trail, and β regulates the influence of the attractiveness function.

Food Existence Probability (∋): This is inversely proportional to time (t) (Liyun et al., 2017). The probability of locating food after it has moved or been blown away is given by:

$$\ni = \frac{\pi r^2 * \theta}{\pi R^2 * 360} \forall \quad [5]$$

where Θ is the search angle ($0° < \Theta \leq 180°$) and τ_{ij} is the probability of pheromone deposited on the path from node i to node j.

This algorithm is also providing the best suited optimized parametric function of output voltage of fuel cell, in this research work this algorithm was tried to modify by changing the state of food particle from stationary to moving and then do a comparative analysis of outcome with earlier values which was defined by ACO technique, this is further elaborated in chapter 4.

1.2.3.4 Grey Wolf Optimization in PEMFC

Grey Wolf Optimization (GWO) is a nature-inspired meta-heuristic optimization algorithm developed by Mirjalili et al. in 2014. It mimics the social hierarchy and hunting behaviour of grey wolves in the wild. In GWO the first step of iteration starts with 'Pack Hierarchy' in which the algorithm uses the social structure of wolves, which includes alpha, beta, delta, and omega wolves. The alpha wolf is the leader, followed by the beta and delta wolves, and finally the omega wolves. Then the next step is 'Hunting Behaviour' in which the algorithm simulates the wolves' hunting behaviour, which involves searching for prey, encircling it, and attacking it. After this step potential solutions to the optimization problem are represented as wolves in the search space. Steps are repeated until a stopping criterion is met, such as a maximum number of iterations or a desired level of convergence. The best solution is returned as the optimal position of the alpha wolf (Yang et al., 2014). This metaheuristic algorithm is also taken into consideration for comparative analysis of parametric function with dynamic ant colony optimization as stated in chapter 4.

1.2.4 ANN modelling and novel metaheuristic algorithm in PEMFC

Metaheuristic algorithms have emerged as powerful tools for optimizing various aspects of fuel cell systems. These algorithms are capable of efficiently handling intricate optimization issues by utilizing the concepts of natural phenomena. As fuel cell technology continues to advance, the application of metaheuristic algorithms will play a crucial role in realizing the full potential of this clean energy source. In this chapter, the important two novel optimization technique have been discussed for the application in PEMFC in the sections 1.2.4.1 and 1.2.4.2.

1.2.4.1 Dynamic Ant Colony Optimization (DACO)

In previous section Ant Colony Optimization has been discussed where it was stated how this optimization technique uses the foraging behaviour of ant in search of food particle, the main difference of dynamic ant colony optimization technique from ACO is the dynamic movement of food particle (Routh et al., 2022), where the food particle is not stationery and it is changing its position over time. The DACO optimization proves better convergence of result compare to ACO as its parametric function when passes through Ballard V Fitness function provides more refined results (Ghosh et al., 2024). The fitness factor, or fitness function, in metaheuristic algorithms is a critical component that evaluates how close a given solution is to the optimum solution of the problem. It's essentially a measure of quality or goodness of a solution within the search space. Here's a brief explanation, the main role of fitness function in Metaheuristic Algorithms (Martins et al., 2021) are 'selection' in which the solutions with better fitness values are more likely to be selected for reproduction or to be part of the next generation, 'search guidance' that helps guide the search towards regions of the search space with higher quality solutions, and 'adaptation' where the fitness function can be adapted or modified to handle multiple objectives or constraints. In this literature will further go through this optimization technique in chapter 4, where the outcome of this algorithm shows better result than another metaheuristic algorithm.

1.2.4.2 Wild Chimpanzee Hunting Optimization (WCHO)

Chimpanzees lived in groups and are incredibly intelligent animals. Although wild chimpanzees typically eat fruits and wild roots, they occasionally hunt other small monkeys (Fathy et al., 2021). It can detect any movement in the tree branches thanks to its extremely keen eyes. The hunting behaviour of monkeys follows a systematic process when pursuing their prey. By studying the hunting behaviour of wild chimpanzees, an optimization technique that mimics their hunting behaviour was created.

$$T_{ij}^{X} = 2\pi\sqrt{\frac{m}{k_{ij}}} \qquad \begin{cases} m \text{ is the mass of the prey / predator} \\ k \text{ is the force per unit displacement} \end{cases}$$

Probability of choosing branch $T_{ij}^{X} = \frac{2\pi\sqrt{\frac{m}{k_{ij}}}}{\sum_{l=0}^{n} h \in all\ path\ 2\pi\sqrt{\frac{m}{k_{ih}}}} * \alpha$ [6]

where $\alpha = \begin{cases} 0 \text{ when wind is blowing} \\ 1 \text{ when wind is not blowing} \end{cases}$

This algorithm provides quite more optimized result in convergence curve of output parameter though the iteration time was higher compare to DACO but still this optimization is applicable for some special stances (Yang et al., 2014). The detailed study of this algorithm along with its application in optimization of fuel cell has been discussed in chapter 5.

1.3 Summary

From the above discussion it can be seen that the PEMFCs have attracted a lot of research attentions in the scientific research community due to its low operational temperature and high efficiency during operation. PEMFCs are incredibly effective electrochemical energy conversion technologies that can transform the chemical energy of hydrogen into electrical and thermal energy without burning it or emitting any air pollutants.

Furthermore, it is very important to utilize the most optimum power output of PEMFC and for this specific reason different methods of metaheuristic algorithm technique as well as ANN have been used and a study has been provided here to get most optimized result. DACO and WCHO are two novel optimization techniques introduced in further research and tried to observe the optimization of output of PEMFC. Some interesting conclusions have been drawn which will be explored in upcoming chapters (Ghosh et al., 2019).

Optimizing Proton Exchange Membrane Fuel Cells (PEMFCs) involve several strategies to enhance their performance, efficiency, and longevity. One key method is material optimization, where advanced materials for the membrane, catalysts, and electrodes are used to improve overall efficiency. Thermal management is also crucial in maintaining optimal temperatures through effective cooling techniques in ensuring better performance. Additionally, refining control strategies for parameters like current density and airflow using advanced algorithms can stabilize and enhance system responses. Integrating PEMFCs with other energy sources, such as batteries or supercapacitors, create hybrid systems that manage power demands more effectively. Moreover, optimizing the design of the fuel cell system, including component layout and subsystem integration, can reduce costs and improve efficiency. Advanced modelling and simulation tools also play a significant role by identifying optimal operating conditions and predicting system behaviour. Researchers can create PEMFC systems that are more dependable and efficient by concentrating on these areas, increasing their viability for use in clean energy applications (Ghosh et al., 2024, Routh et al., 2023).

PEMFC cell has many controlling parameters by which it can be optimized in great and efficient manner, by using different approaches from manual operating to advanced methods such as artificial neural networks, meta heuristic algorithms, artificial intelligence, machine learnings, and deep learning methods (Dorigo et al., 2012).

In the next chapter, different studies and reports will be discussed that will help understand the behaviours of the PEMFC and find a better approach that will be useful in optimizing the fuel cell in efficient manner. This literature review will help in comparing various optimization technique on ANN and meta heuristic algorithms and also will help to meet the proposed research objective.

CHAPTER 2

Literature Review

A Comparative Study on Artificial Neural Network-Based Multi-Objective Optimization for Proton Exchange Membrane Fuel Cell. *RASAYAN Journal of Chemistry*,*17*(02),576–587.

In the previous chapter, it was explored about Proton Exchange Membrane Fuel Cell (PEMFC). In this chapter the detailed literature review has been carried out on the approaches and algorithms to optimize PEMFC under simulated environmental condition. Initially the application of Artificial Neural Networks (ANNs) for PEMFC has been described followed by metaheuristic approach. These two techniques are powerful tools used for optimization and modelling in various fields. ANNs, inspired by the human brain's neural networks, consist of interconnected neurons organized in layers and are trained to learn patterns from data, making them effective for predictive modelling and complex problem solving (Smith et al., 2010). Metaheuristic algorithms, on the other hand, are high-level strategies designed to explore and exploit the solution space of optimization problems efficiently. They include techniques like Genetic Algorithms, Simulated Annealing, and Particle Swarm Optimization, which are particularly useful when exact methods are impractical due to the problem's complexity (Ting et al., 2014). The combination of these two approaches can lead to more robust and efficient solutions, as demonstrated by their applications in fields like engineering and machine learning (Kim et al., 2021).

Before the advent of neural networks (NNs) and metaheuristic algorithms, PEMFCs were controlled using traditional methods such as Proportional-Integral-Derivative (PID) controllers and model-based control methods. PID controllers were widely used due to their simplicity and effectiveness in maintaining system stability by adjusting control inputs based on error values. Model-based control methods, such as Internal Model Control (IMC), Model Predictive Control (MPC), and Nonlinear Model Predictive Control (NMPC), were employed to handle the complex dynamics of PEMFC systems by using mathematical models to predict and optimize system behaviours (Yang et al., 2016). These traditional methods provided a foundation for PEMFC control but often struggled with the nonlinearities, time-varying nature, and uncertainties inherent in PEMFC systems. The introduction of NNs and metaheuristic algorithms has significantly enhanced the ability to model, predict, and optimize PEMFC performance, leading to more efficient and reliable control strategies (Routh et al., 2022).

2.1 Overview of literature review

Designing linear model may lead to ignorant of physical quantities that are active only during the phase transition of the electro chemicals, which may lead to poor performance but significantly reduce the cost of the model taken for the evaluation. However, designing of the more complex model can lead to the complexed structure and inestimable cost. Example, designing of complexed non-linear model with multi-layered PEM fuel cell. The dynamic behaviour of the non-linear PEM fuel cell cannot be well represented by first-order differential equations. Many PEMFC non-linear models are discussed in the subsequent sections.

Eberhart et al., (1995) have introduced Particle Swarm Optimization (PSO), a metaheuristic optimization algorithm inspired by the social behaviours of birds and fish. The algorithm involves a population of particles that move through the search space to find optimal solutions. Each particle adjusts its position based on its own experience and the experience of neighbouring particles, effectively balancing exploration and exploitation. PSO has proven to be a versatile and efficient optimization technique applied across various fields.

Lučić et al., (2003) proposed Bee Colony Optimization (BCO) algorithm, a metaheuristic algorithm inspired by the foraging behaviours of honey bees. This algorithm mimics the way bees search for food by employing a combination of local and global search strategies. Artificial bees explore the solution space and share information about the quality of found solutions through a process similar to the waggle dance. BCO effectively balances exploration and exploitation, making it a valuable tool for solving complex optimization problems, particularly in the field of transportation engineering.

Dorigo et al., (2004) discussed Ant Colony Optimization (ACO), a metaheuristic inspired by the foraging behaviours of ants. The algorithm involves artificial ants that simulate the natural pheromone trail-laying and following behaviours of real ants to find optimal solutions. By iteratively building and improving solutions, ACO effectively balances exploration and exploitation, making it a powerful tool for solving various optimization problems.

Sisworahardjo et al., (2010) described the multilayer feed forward ANN, used to train the portable PEM fuel cell model by using backpropagation training algorithm. The ANN works with four fully connected layers and two hidden layers. The PEM fuel cell ANN model is trained by comparing the data gathered from the experiment and calculated values.

Cheng et al., (2015) started the nonlinear autoregressive moving average model with exogenous inputs (NARMAX) approach employed to analyze time-frequency domains for the proton exchange membrane fuel cell (PEMFC) system. The NARMAX model is designed from the experimental measured input data and output data.

Eusuff et al., (2008) reported the Shuffled Frog-Leaping Algorithm (SFLA), a metaheuristic optimization technique inspired by the natural behaviours of frogs searching for food. It combines both local and global search strategies to effectively solve complex optimization problems. The algorithm's ability to shuffle and regroup frogs helps in avoiding local optima and ensures a thorough search of the solution space. SFLA has demonstrated its efficacy in solving complex optimization problems across various engineering and scientific domains.

Dalasm et al., (2011) described an artificial neural network approach together with statistical methods (ANOM and ANOVA methods) for modelling, prediction, and analysis of an agglomerate cathode catalyst layer (CL) performance.

Nanadegani et al., (2020) proposed the neural network modelling to maximize the power output of PEM fuel cells by considering the various operating conditions such as operating temperature, relative humidity, stoichiometry at the cathode and anode sides at a constant pressure of 1 bar. Performance of the PEM fuel cell increases with low current but decreases with high current due to the increase in the partial pressure of the water vapor as the temperature increases and dryness of the membrane.

Mirjalili et al., (2021) studied the optimization technique to find the best solution among possible ones for problems like timetabling, path planning, and engineering design. To improve performance, chaos theory is used in metaheuristic optimization. Chaotic maps help balance exploration and exploitation, improving local optima avoidance and convergence speed.

Wang et al., (2021) described an air coolant PEM fuel cell structure with limited volume comprising of strong coupling between the supplied air and the coolant resulting in difficulty analyzing the relationship between optimal power and stack temperature, yielding to a low power efficient model.

Na et al., (2007) reported the performance optimization method for PEMFC using grey correlation analysis and the response surface method. The grey correlation analysis can convert the multi-objective optimization to a single objective optimization problem, helping determine the optimal design of hydrogen fuel cells.

Ang et al., (2010) analyzed the optimization model with a general polymer electrolyte membrane (PEM) fuel cell system for attaining efficiency and size trade-offs. The weighting method is used to perform the multi-objective optimization, using different stack output power to generate Pareto sets. The Pareto set is required for plotting optimal efficiency and the area of the membrane electrode assembly (MEA), giving a quantitative description of the trade-off between size and efficiency.

Saengrung et al., (2007) proposed a commercial PEM fuel cell using two ANN approaches. Two artificial neural networks, including the back-propagation (BP) and radial basis function

(RBF) networks, were constructed, tested, and compared. The back-propagation (BP) network was investigated by varying error goals, the number of neurons, the number of layers, and training algorithms.

Kandidayeni et al., (2021) described online system identification (OSI) for estimating the time-varying parameters of a well-known PEMFC semi-empirical model, comparing the characteristics of a 500-W Horizon PEMFC and its performance with a Kalman filter perceived as a reliable linear estimator.

Wilberforce et al., (2022) started working with a Polymer Electrolyte Membrane fuel cell (PEMFC) capable of handling the multivariable nonlinear performance of the PEMFC. The model performances are based on ANN using two different learning algorithms to estimate the stack voltage and power. The models have consistently shown to be comparable to the experimental data.

Tsai et al., (2023) introduced a novel metaheuristic algorithm called DHOA, inspired by human deer hunting behaviours. Each hunter, designated as leader and successor, updates their position based on their hunting strategy until they capture the deer. Experimental results indicate that DHOA performs competitively against other optimization algorithms like GWO, WOA, FF, and PSO.

The above various models inherently complex in nature when apply in PEMFC due to its non-linear behaviour. The non-linear models are also prone to less accurate due to the presences of the highly sensitive operating parameters e.g., temperature, humidity, pressures, and fuel composition. Therefore, validating nonlinear models against experimental operational data of PEMFC is difficult due to the differences between theoretical predictions and real-time behaviours. It can be found that the most common meta heuristics algorithms like PSO, ACO, GA are used for non-linear optimization in PEMFC. The ACO can be used widely due to its capabilities to converge towards suboptimal solutions. The performance of ACO is highly dependent on the input parameter settings, which can be difficult to tune. ACO may struggle with very large problem instances. DHOA's performance is also highly dependent on the choice of control parameters. DHOA can be slow to converge, especially in high-dimensional search spaces. PSO can suffer from premature convergence to suboptimal solutions. The performance of PSO is sensitive to the choice of algorithm parameters, such as inertia weight and acceleration coefficients. The draw-back of PSO is that it may not perform well on very large-scale problems. SFLA requires careful tuning of multiple parameters, which can be challenging and time-consuming. The algorithm can sometimes converge prematurely to suboptimal solutions. SFLA may get trapped in local optima, especially when dealing with complex optimization problems. It is found that for large scale problems, SFLA can be computationally expensive for large scale problem (Fathy et al., 2021).

2.2 Application of Neural Network in PEMFC modelling

In the beginning of the year 1943, Warren McCulloch and Walter designed the first ever artificial neuron network which was capable of deciding whether the input data belong to the group of the specific class or not, by using the binary specifiers. First Perceptron uses three layers, namely S- unit (Sensory unit), A-unit (Association unit) and R- unit (Response unit). Rosenblatt name this unit as alpha-perceptron. Later in the book of the Principles of Neurodynamics (1962), Rosenblatt subdivide the perceptron into "cross-coupling", "back-coupling", “four-layer perceptrons” depending upon the connection between the different layers of the perceptron units. McCulloch-Pitts Neuron were the first ever working model of computational neuron, proposed by Warren MuCulloch and Walter Pitts in 1943.

The neuron generates a binary value (0 or 1) based on the weighted sum (each input is associated with a weight, representing the synaptic strength) of its inputs exceeds a certain threshold. The neuron generates (outputs 1) if the weighted sum of inputs is greater than or equal to the value set as thyrsoid; else it generates 0 as output. It provided the first formal model of a neuron and laid the groundwork for the development of more complex neural networks.

The neuron function can be mathematically represented as follows:

$$y = f \sum_{i=1}^{n} Щ_i \, x_i \, \theta \qquad [7]$$

Where:

y is the output of the neuron.

X_i are the inputs.

$Щ_i$ are the weights of the inputs.

Ө is the threshold.

f is the activation function, which in the case of the McCulloch-Pitts neuron is a step function.

McCulloch and Pitts showed that networks of these neurons could perform logical operations like AND, OR, and NOT, demonstrating their potential for computation. Despite its simplicity, the McCulloch-Pitts neuron was a crucial stepping stone in the field of artificial intelligence and neural networks. It helped inspire further research and development, leading to the sophisticated models that has been described here. The model is highly simplified and does not capture the complexities of biological neurons, such as graded potentials or temporal dynamics. The back propagation model also discussed below for the PEMFC Neural Network (NN) modelling (Mossa et al., 2021).

2.2.1 Backpropagation algorithm in ANN for PEMFC

The backpropagation algorithm is a fundamental method used to train artificial neural networks, particularly in supervised learning. It stands for "backward propagation of errors" and works by adjusting the weights of the network to minimize the error between the predicted output and the actual output. The input data is passed through the network, layer by layer, until it reaches the output layer. During this phase, the network makes predictions based on the current weights (Smith et al., 2010). The error is calculated by comparing the network's predicted output with the actual output (often using a loss function, such as mean squared error or Cross-Entropy). The error is propagated back through the network from the output layer to the input layer. This involves calculating the gradient of the error with respect to each weight using the chain rule of calculus. The weights are updated to reduce the error. This is typically done using gradient descent, where each weight is adjusted by subtracting a fraction of its gradient (learning rate).

The feed forward mechanism can be mathematically represented as

$$y = f(\text{Щ}.x + b) \qquad [8]$$

Where:

Щ is the weight matrix

X is the input vector

b is the bias

f is the activation function

If $y^{\wedge}$ is the predicted output and y is the actual output, the error (loss) EE can be computed using a loss function, such as Mean Squared Error:

2.3 Types of Artificial Neural Networks

2.3.1 Feed Forward Neural Networks

Feedforward Neural Networks (FNNs) are the simplest type of artificial neural network architecture. In an FNN, the information moves in only one direction—from the input layer, through the hidden layers (if any), to the output layer. There are no cycles or loops in the network. FNNs are widely used for pattern recognition and classification tasks (Michelucci et al., 2022, Goodfellow et al., 2016).

Multiple layer design of FNN, where each layer consists of multiple neurons, and the connections between neurons, are weighted and analyzed. The input layer receives the initial data, the hidden layers process the data through activation functions, and the output layer produces the final result as shown in figure 2.1 (Michelucci et al., 2022).

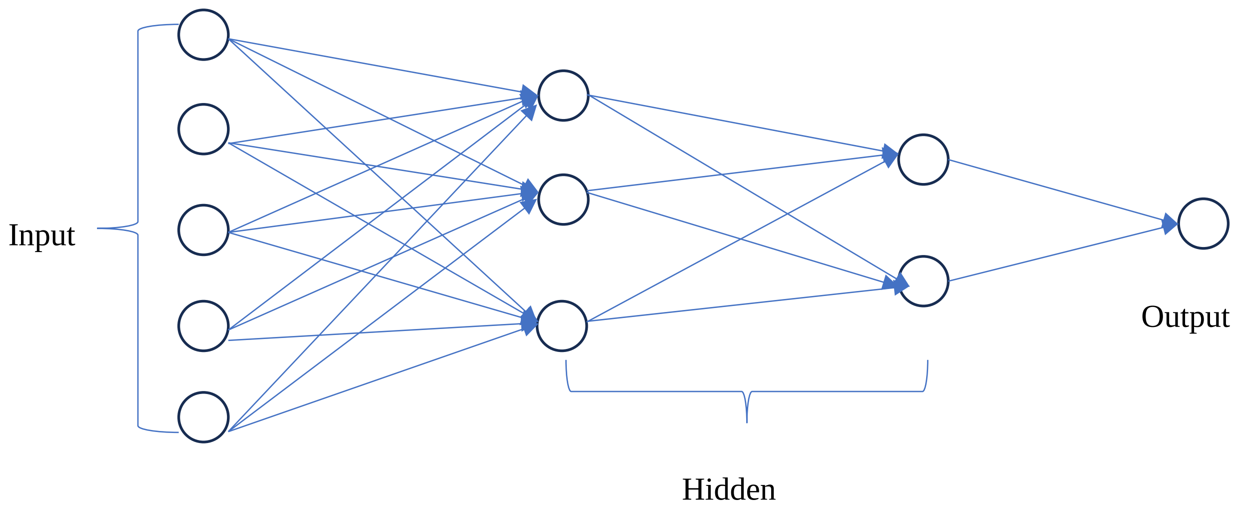

Figure 2.1 Multiple layer design of FNN

2.3.2 Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNNs) are a class of deep neural networks, most commonly applied to analysing visual imagery. CNNs use a variation of multilayer perceptron's designed to require minimal pre-processing. They are known for their ability to automatically and adaptively learn spatial hierarchies of features from input images (Dhillon et al., 2020, Krizhevsky et al., 2012).

2.3.3 Recurrent Neural Networks (RNNs)

Recurrent Neural Networks (RNNs) are a class of neural networks where connections between nodes form a directed graph along a temporal sequence. This allows them to exhibit temporal dynamic behaviour and use their internal state (memory) to process sequences of inputs. RNNs are particularly useful for tasks such as speech recognition, language modelling, and time series prediction (Alzubaidi et al., 2021, Hochreiter et al., 1997).

2.4 Training of Artificial Neural Networks

Supervised learning: In supervised learning, artificial neural networks (ANNs) are trained on labelled data, with each input paired with its corresponding output. The network learns to map these inputs to the correct outputs by minimizing the error between the predicted and actual results. Common algorithms used in this process include backpropagation and stochastic gradient descent (Bengio et al., 2015).

Unsupervised learning: In unsupervised learning, ANNs are trained on unlabelled data. The main objective is to identify patterns and structures within the data without explicit guidance. Techniques such as K-means clustering and autoencoders enables grouping similar data points and learn efficient data representations respectively, are commonly employed (Goodfellow et al., 2016).

Reinforcement Learning: Reinforcement learning involves training an ANN to make decisions within an environment by interacting with it and receiving feedback in the form of rewards or penalties. The goal is to maximize cumulative rewards over time. Key algorithms include Q-learning and deep Q-networks (DQNs) (Mnih et al., 2015).

Transfer learning: Transfer learning leverages knowledge gained from one task to enhance performance on a related task. By reusing a pre-trained model, training time is significantly reduced, and performance can be improved, especially when labelled data is limited (Yosinski et al., 2014).

Ensemble methods: Ensemble methods combine multiple models to improve overall performance. Techniques involve such as bagging, which trains multiple models on different subsets of the data and averages their predictions, and boosting, which sequentially trains models with each focusing on correcting the errors of the previous ones, are commonly used (Dietterich et al., 2000).

Optimization and regularization: Optimizing hyperparameters like learning rate, number of layers, and number of neurons is crucial for achieving optimal performance. Techniques such as grid search, random search, and Bayesian optimization are employed to explore the hyperparameter space. To prevent overfitting, regularization techniques like L1/L2 regularization, dropout, and early stopping can be used. Batch normalization helps by standardizing inputs to each layer, improving training stability and performance. Learning rate scheduling can also accelerate convergence by adjusting the learning rate during training (Srivastava et al., 2014, Ioffe et al., 2015).

2.5 Integration of ANN and metaheuristic algorithm in PEMFC

Integrating Neural Network Controllers (INNC) with Fuzzy Logic Controllers (FLC) offers a robust solution for managing the active power output of PEM fuel cells. These controllers can precisely adjust hydrogen flow to meet varying load demands, ensuring precise regulation of active power. Simulation studies have confirmed the effectiveness of these controllers in both active and reactive power management, making them suitable for residential applications (Zhang et al., 2018, Kim et al., 2021).

The application of ANNs in real-world scenarios has been validated through extensive simulations. The developed models, including ANN fuel cell stack models, reformer models, and DC/AC inverter models, have been tested using computer-simulated step changes in load active and reactive power demands. These simulations confirm that simultaneous control of converter and fuel quantities is essential for effective power management.

Additionally, the results highlight the potential of NNTC and FLC in enhancing the performance and reliability of fuel cell systems for residential power generation (Mamaer et al., 2012). Table 2.1. shows the performance metrics for different systems using ANN, FLC, and the hybrid ANN-FLC approach. The hybrid system consistently outperforms the individual methods (Mallikarjuna et al., 2020).

Table 2.1 Performance matrices (Jahromi et al., 2021)

SL. No	System	Performance Metrics	ANN	FLC	ANN-FLC Hybrid
1	UPQC	Power Quality	85%	80%	90%
2	MPPT	Efficiency	88%	85%	92%
2	Industrial	Stability	80%	78%	85%

2.5.1 Neural Network applications in fuel cell systems

Neural networks offer a powerful tool for optimizing PEM fuel cell models. Backpropagation feedforward networks have been successfully employed to accurately predict cell voltage. By extending this approach to other system components, researchers can develop comprehensive system models that enable efficient simulation of complex system behaviour, leading to improved design, optimization, and control of fuel cell systems (Smith et al., 2010, Lee et al., 2020).

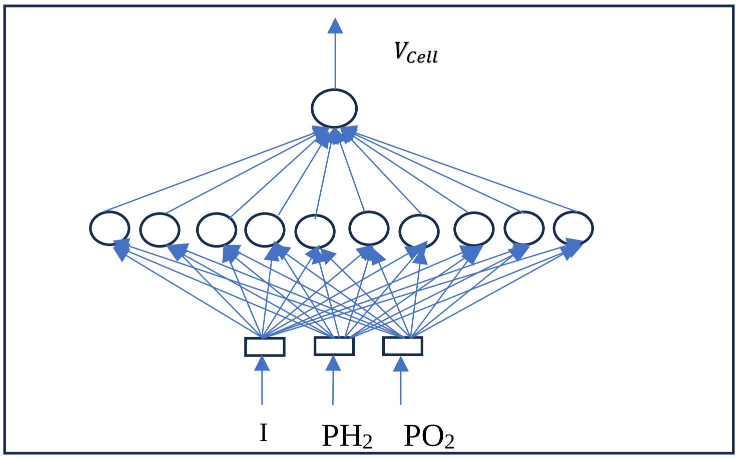

Figure 2.2 PEMFC NNT model

Figure 2.2. show the improved version INNC model (Kahia et al., 2023). The study illustrates a novel technique to increase the service life and understand the aging mechanisms in PEMFC systems by modifying air flow rate and humidifying gases. The proposed model uses neural networks to estimate and diagnose the state of health of the fuel cell under various operating condition.

2.5.2 Meta-heuristic algorithm in PEMFC

Metaheuristic algorithms are crucial for addressing complex optimization problems due to their unique capabilities and advantages. Traditional optimization methods often fall short when dealing with large, intricate problem spaces. In contrast, metaheuristics offer flexibility and adaptability, making them suitable for a wide range of applications across various domains. Their global search capability allows them to explore the solution space thoroughly, significantly increasing the likelihood of finding global optima rather than getting trapped in local optima (Ting et al., 2014). These algorithms also incorporate heuristic guidance, which helps them efficiently navigate vast search spaces and find high-quality solutions within a reasonable timeframe. Moreover, metaheuristics can be parallelized, leveraging modern multi-core processors and distributed computing environments to enhance problem-solving efficiency. By adapting their search strategies based on problem characteristics and search progress, metaheuristics improve their effectiveness over time (Tsai et al., 2023). These features collectively make metaheuristic algorithms indispensable tools for optimizing complex systems, such as scheduling, routing, and resource allocation, where traditional methods might struggle.

The ACO can sometimes converge to suboptimal solutions. The performance of ACO is highly dependent on the parameter settings, which can be difficult to tune. ACO may struggle with very large problem instances. Similar to ACO, DHOA's performance is highly dependent on the choice of control parameters. DHOA can be slow to converge, especially in high-dimensional search spaces (Singla et al., 2021). It may get stuck in local optima, especially in complex landscapes. PSO can suffer from premature convergence to suboptimal solutions. The performance of PSO is sensitive to the choice of parameters, such as inertia weight and acceleration coefficients. PSO may not perform well on very large-scale problems (Mirjalili et al., 2021). SFLA requires careful tuning of multiple parameters, which can be challenging and time-consuming. The algorithm can sometimes converge prematurely to suboptimal solutions. SFLA may get trapped in local optima, especially when dealing with complex optimization problems. For large-scale problems, SFLA can be computationally expensive. Table 2.2 shows the generalized time and space complexity of different type of meta heuristic algorithms. Space Complexity refers to the amount of memory space required by an algorithm to run to completion. It measures how the memory usage grows with the input size.

Table 2.2 Space and time complexity of different types of algorithms

SL No	Algorithm	Time Complexity Function	Space Complexity Function
1	PSO (Eberhart et al., 1995)	$O(n^2)$	$O(n)$
2	BCO (Lučić et al., 2003)	$O(n^2)$	$O(n)$
3	ACO (Dorigo et al., 2004)	$O(n^2)$	$O(n^2)$
4	SFLA (Eusuff et al., 2008)	$O((n^2)$	$O(n^2)$
5	DHOA (Tsai et al., 2023)	$O(n^2)$	$O(n)$

$O(n^2)$: Quadratic function

$O(n)$: Linear function

Time Complexity refers to the computational time taken by an algorithm to run, as a function of the size of the input. It measures how the execution time grows with the input size.

Understanding time and space complexity helps in designing efficient algorithms that perform well with large inputs. It ensures that algorithms can scale effectively as the problem size increases. It helps in managing computational resources effectively, especially in systems with limited memory or processing power. Provides a way to analyses and compare the performance of different algorithms.

Demands of clean and feasible energy from the PEMFC compelled the abolitions of the traditional methods for tuning the PEMFC and introduced the methods of modern approaches where the parameters can be tuned using different types of algorithms. This algorithm uses the technique of brute forcing the parameters to find the optimum combination of parameters to generate feasible energy from the PEMFC. However, these algorithms were not sufficient to optimise the parameters of fuel cell as the parameter sizes increases the time and space complexity of the algorithm increases which result in the infinite number of the looping through the parameter which ultimately leads to non-feasible solution and abolition of such methods.

Metaheuristics algorithms are designed to explore a large search space and find near-optimal solutions efficiently. Neural networks, on the other hand, are more focused on exploiting patterns in data to make predictions or classifications (Eberhart et al., 1995). Metaheuristics algorithms are particularly effective for solving optimization problems, such as scheduling, routing, and resource allocation (Lučić et al., 2003). Neural networks are not inherently designed for these types of problems (Dorigo et al., 2004).

Metaheuristic algorithms can be used to optimize the parameters of neural networks, improving their performance. This hybrid approach leverages the strengths of both methods (Eusuff et al., 2003). Metaheuristic algorithms are good at avoiding local optima and finding global optima in complex landscapes (Tsai et al., 2023). Neural networks can sometimes get stuck in local optima, especially in high-dimensional spaces (Eberhart et al., 1995). Metaheuristics can be adapted to a wide range of problems and domains, making them versatile tools for optimization.

Neural networks require specific architectures and training data tailored to the problem at hand (Dorigo et al., 2004).

Neural networks are excellent tools for learning and prediction but, metaheuristic algorithms offer the essential optimization capabilities needed to tackle complex problems effectively. By integrating these approaches, more robust and comprehensive solutions can be achieved.

2.6 Application of Frog Leap Algorithm in PEMFC

Metaheuristic optimization technique inspired by the natural behaviour of frogs searching for food. It combines both local and global search strategies to effectively solve complex optimization problems. The Shuffled Frog-Leaping Algorithm (SFLA) is a robust metaheuristic optimization technique that effectively combines local and global search strategies (Eusuff et al., 2008). Inspired by the foraging behaviour of frogs, it efficiently explores and exploits the search space to find optimal solutions. The algorithm's ability to shuffle and regroup frogs helps in avoiding local optima and ensures a thorough search of the solution space. SFLA has demonstrated its efficacy in solving complex optimization problems across various engineering and scientific domains. Its versatility and effectiveness make it a valuable tool for addressing challenging optimization tasks. Here the evolution of the Frog Leap Algorithm is presented in figure 2.3.

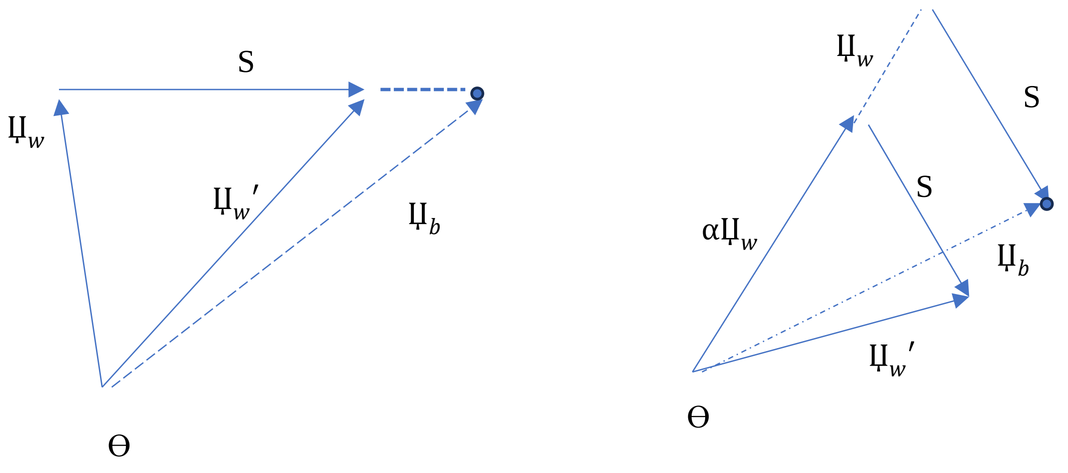

Figure 2.3 Frog Leap Rule (left) Modified Frog Leap Rule (right)

The original frog leap can be expressed as:

$$\text{Џ}_w{}' = \text{Џ}_w + S \qquad [9]$$

Where:

Џ_w represents the position of a frog in the search space.

S is the step size or the leap distance determined by the algorithm.

and Modified frog leap can be expressed as:

$$\text{Џ}_w{}' = \alpha\text{Џ}_w + S \qquad [10]$$

Where:

α is a scaling factor or adjustment coefficient.

Џ_w is the original position of the frog.

S is the step size or the leap distance.

where *S* is the updated step size and is a *D*-dimensional vector; *r* is a random number between 0 and 1; S_{max} is the maximum step size allowed to be adopted by a frog after being infected.

2.7 Fuel cell stack optimization

Design optimization is an engineering methodology that uses mathematical formulations to find the best design among many alternatives. This process entails establishing design variables, identifying an objective function for optimization (either maximization or minimization), and ensuring that the design adheres to specified constraints.

Design Variables: Parameters that define the design alternatives.

Objective Function: A functional combination of design variables that needs to be optimized.

Constraints: Conditions that the design must satisfy, expressed as equalities or inequalities.

Design optimization is used in various fields such as structural design, aerodynamic shape optimization, and architectural design. It helps in achieving the best performance while adhering to constraints and requirements (Martins et al., 2021).

Stack Design:

A fuel cell stack consists of multiple individual cells stacked together, with the cathode of one cell connected to the anode of the adjacent cell. This configuration ensures that the same current passes through each cell.

Components: The main components include membrane electrode assemblies (MEAs), gaskets, bipolar plates with electrical connections, and end plates. These components are clamped together using bolts, rods, or other methods.

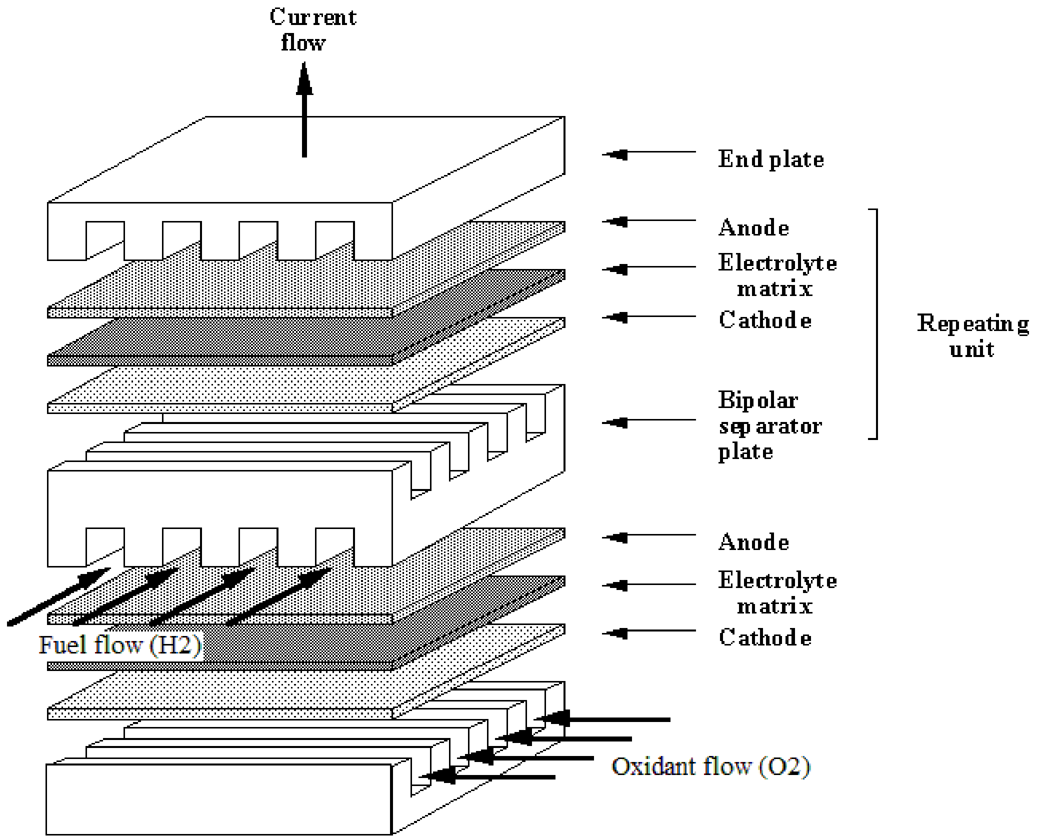

Figure 2.4 Orthogonal sectional view of fuel cell

Design Considerations: Key considerations in stack design include managing thermal expansion, minimizing pressure drop, ensuring uniform reactant distribution, and preventing water accumulation. The design should also account for manufacturability and ease of assembly (Barbir et al., 2012). The figure 2.4 shows the orthogonal view of fuel cell which can helps to understand fuel and oxidant flow management and its optimization.

2.8 PEMFC operating condition optimization

Temperature: The operating temperature significantly affects the performance and efficiency of fuel cells. Optimal temperature ranges vary depending on the type of fuel cell, but maintaining the right temperature is crucial for maximizing power output and ensuring durability.

Pressure: Operating pressure impacts the reaction rates within the fuel cell. Proper management of pressure can enhance performance and reduce degradation.

Flow Rates: The flow rates of reactants (hydrogen and oxygen) need to be optimized to ensure efficient fuel utilization and prevent flooding or drying of the membrane.

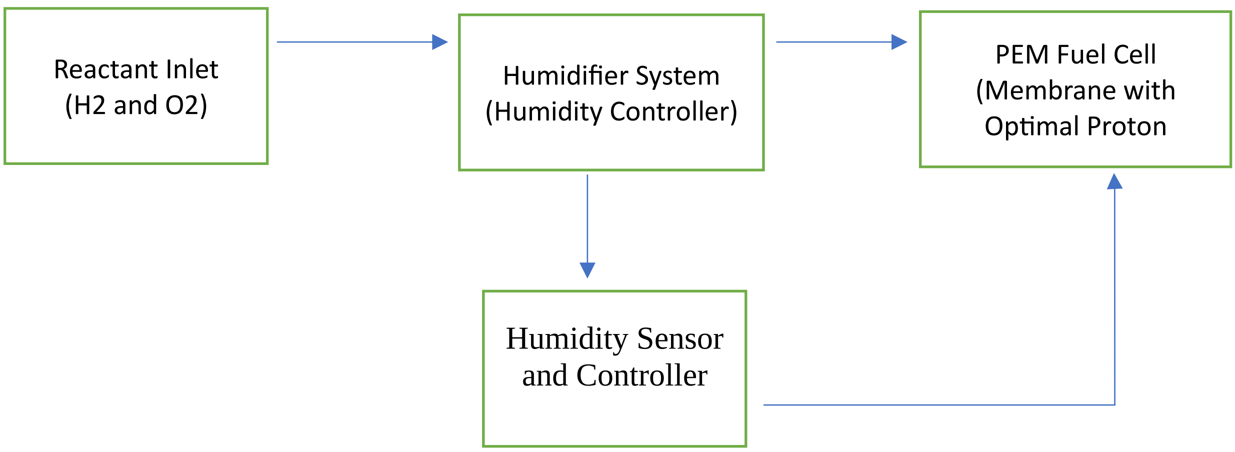

Figure 2.5 Humidity controller of PEMFC

Humidity: Controlling the humidity of the reactants is essential for maintaining membrane hydration and ensuring optimal proton conductivity (Liao et al., 2024). Humidity controller of PEMFC is shown in figure 2.5.

Electrodes: The electrodes must efficiently facilitate the electrochemical reactions. Optimizing the microstructure and composition of the electrodes can enhance the reaction kinetics and reduce ohmic losses.

To reduce ohmic losses in a PEMFC, the Butler-Volmer equation for activation losses and the Ohmic loss equation for electrical resistance losses can be referred.

Butler-Volmer Equation for Activation Losses:

The Butler-Volmer equation describes the relationship between the current density (i) and the overpotential ∈.

$$i = i_0 \left\{ e^{\frac{\alpha_\alpha F_\epsilon}{RT}} - e^{-\frac{\alpha_c F_\epsilon}{RT}} \right\} \quad [11]$$

Where:

i_0 is the exchange current density

α_α and α_c are the anodic and cathodic charge transfer coefficients, respectively

F is the Faraday constant

R is the gas constant

T is the temperature in Kelvin

∊ is the overpotential

Ohmic losses are due to the resistance to the flow of electrons and ions in the fuel cell components. The ohmic loss can be represented as:

$$\in_{ohmic} = i. R_{total} \quad [12]$$

Where:

i is the current density.

R_{total} is the total resistance, which includes the resistance of the membrane, electrodes, and interconnects.

To optimize the PEMFC, need of minimization is required for both activation and ohmic losses:

$$\in_{total} = \in_{activation} \in_{ohmic} \quad [13]$$

reducing the overpotential and optimizing the resistance, the overall performance of the PEMFC can be improved.

Durability: Enhancing the durability of MEAs involves developing materials that resist degradation over time. This includes improving the stability of catalysts and membranes under operational conditions.

2.9 Controller optimization in PEMFC

2.9.1 Optimization using voltage controller

PID Control: Proportional-Integral-Derivative (PID) control is widely used for its simplicity and effectiveness in maintaining stable voltage.

Model Predictive Control (MPC): MPC uses a model of the PEMFC to predict future outputs and adjust control inputs accordingly, optimizing voltage control.

Sliding Mode Control (SMC): SMC is robust to system uncertainties and disturbances, making it suitable for voltage control in PEMFCs.

Dynamic Integral Sliding Mode Control (DISMC): DISMC combines dynamic and integral sliding mode control to enhance voltage regulation under varying load conditions.

Deep Deterministic Policy Gradient (DDPG): This advanced control method uses reinforcement learning to optimize voltage control, improving robustness and performance (Wu et al., 2020)

2.9.2 Optimization using temperature controller

Air-Cooled Systems: Utilizes fans to dissipate heat through convection.

Liquid-Cooled Systems: Uses coolant fluids to absorb and transfer heat away from the fuel cell.

Phase-Change Cooling Systems: Employs phase-change materials that absorb heat by changing phase (e.g., from solid to liquid). A schematic view of cooling system in PEMFC is shown in figure 2.6.

Control Strategies: Advanced control strategies like PID control, fuzzy logic control, and model predictive control (MPC) are used to manage temperature effectively.

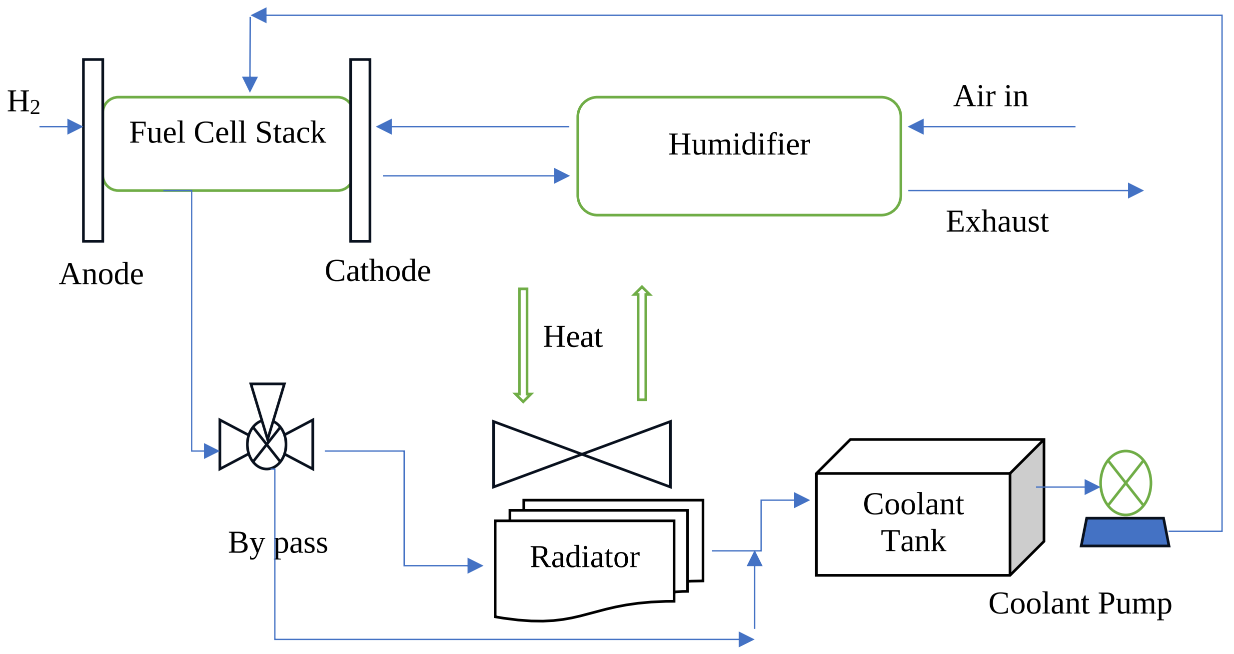

Figure 2.6 Basic cooling system of PEMFC

2.9.3 Water flooding management using controllers

Gas Flow Management: Optimizing the flow rates of reactant gases (hydrogen and oxygen) to ensure proper water removal and prevent flooding.

Humidity Control: Controlling the humidity levels of the incoming gases to maintain the right balance of membrane hydration.

Flow Field Design: Designing flow fields and channels to facilitate efficient water removal and prevent water accumulation.

Thermal Management: Using cooling systems to manage the temperature and prevent excessive water evaporation or condensation.

Advanced Control Algorithms: Implementing control algorithms like PID control, model predictive control (MPC), and reinforcement learning methods to dynamically manage water levels (Xiang et al., 2024).

2.10 Fault diagnosis and prognosis in PEMFC

Fault Diagnosis Method for PEMFCs Using PSO-DBN:

Sensors collect data from the PEMFC stack, including voltage, current, temperature, and humidity levels. Principal Component Analysis (PCA) is applied to reduce the dimensionality of the data, improving training efficiency and focusing on the most significant features. A Deep Belief Network (DBN) is optimized using Particle Swarm Optimization (PSO) to train the model. This involves multiple layers of Restricted Boltzmann Machines (RBMs) which are pre-trained in an unsupervised manner. The pre-processed data is fed into the PSO-DBN model. The PSO algorithm adjusts the weights of the DBN to minimize the error rate, improving diagnostic accuracy.

The trained PSO-DBN model analyses new data from the PEMFC stack to detect and diagnose faults. The model classifies the type and location of the fault with high accuracy.

The model can also predict the remaining useful life (RUL) of the PEMFC components, allowing for proactive maintenance. This method is highly used to diagnostic accuracy and can effectively manage the health and reliability of PEMFC systems (Zhu et al., 2024).

2.10.1 Fault detection algorithms

This is used identify and classify faults in systems, enhancing reliability and efficiency. Algorithms like Particle Swarm Optimization (PSO), Genetic Algorithms (GA), Ant Colony

Optimization (ACO), and Whale Optimization Algorithm (WOA) are used to optimize fault diagnosis processes. These algorithms are applied to various domains, including industrial machinery, electrical systems, and IoT devices, to detect and diagnose faults accurately (Zhu et al., 2024).

2.10.2 Prognostic health management (PHM)

PHM is a system engineering discipline focused on assessing the current health of a system and predicting its future condition. The goal is to improve system reliability, reduce maintenance costs, and extend the lifespan of components and systems. This monitoring system parameter is used to detect any deviations from normal operation, identifying the root cause of any detected anomalies.

Maintenance Decision-Making: Making informed decisions on maintenance actions based on the prognosis (Gharib et al., 2023).

2.11 Tuning of algorithm parameter

Algorithm Parameter Tuning involves adjusting the parameters of an algorithm to optimize its performance. This process is crucial in machine learning and optimization, as the right parameter settings can significantly improve the accuracy and efficiency of the model or algorithm.

Hyperparameters: These are parameters that are set before the learning process begins and cannot be learned from the data. Examples include learning rate, number of hidden layers, and batch size.

Optimization Techniques: Common techniques include Grid Search, Random Search, Bayesian Optimization, and Gradient-based optimization.

Importance: Proper tuning can lead to better model performance, faster convergence, and improved generalization to new data (Pandian et al., 2024).

2.11.1 Tuning model accuracy

Model Accuracy is a metric used to evaluate the performance of a predictive model by measuring the proportion of correct predictions made out of all predictions. It is calculated as:

$$\text{Accuracy} = \frac{Number\ of\ Correct\ Predictions}{Total\ Number\ of\ Predictions} \qquad [14]$$

Proportion of Correct Predictions: Accuracy quantifies how often the model makes correct predictions. In binary classification, accuracy is the fraction of correctly identified positive and negative instances. Accuracy alone can be misleading, especially with imbalanced datasets. Other metrics like precision, recall, and F1-score are often used alongside accuracy to provide a more comprehensive evaluation.

Model accuracy (Abbassi et al., 2023) in PEM fuel cells (PEMFCs) is essential for optimizing performance and ensuring reliable operation. Accurate models help predict fuel cell behaviour under various conditions, which aids in designing effective control strategies. Accurate estimation of key parameters such as reaction rates, membrane conductivity, and gas diffusion coefficients is crucial. PEMFC models often involve nonlinear relationships, making accurate modelling. Techniques like multi-strategy optimization algorithms (e.g., Dandelion Optimizer, Atomic Orbital Search) are used to improve model accuracy.

A common metric for evaluating model accuracy is the Mean Absolute Percentage Error (ŋ), given as:

$$ŋ = \frac{1}{2}\sum_{i=1}^{n} \left| \frac{X_{i} - \hat{X}_{i}}{X_{i}} \right| \times 100 \qquad [15]$$

Where:

n is the number of observations

X_i is the actual value

$\hat{X}_i$ is the predicted value

This equation helps quantify the accuracy of a PEMFC model by comparing the predicted values to the actual observed values.

Sum of Squared Errors (δ) for Parameter Estimation (Tummala et al., 2024).

Which can be expressed as:

$$\delta = \sum_{i=1}^{n} (X_{i\_}\hat{X}_i)^{2} \tag{16}$$

Where:

n is the number of observations

X_i is the actual value

$\hat{X}_i$ is the predicted value

Above equations are commonly used to measures the accuracy of PEM fuel cell models by comparing predicted values to actual experimental data.

2.12 Multi-Objective Optimization algorithms

Multi-Objective Optimization (MOO) involves optimizing two or more conflicting objectives simultaneously. This approach is essential in real-world problems where trade-offs between different objectives need to be considered. Solutions are evaluated based on Pareto optimality, where no objective can be improved without worsening another. MOO is used in various fields such as engineering design, economics, logistics, and environmental management. Common techniques include evolutionary algorithms, swarm intelligence, and hybrid methods combining multiple optimization strategies (Pereira et al., 2022).

In Multi-Objective Optimization (MOO), the concept of Pareto Optimality is used to find the optimal trade-offs between conflicting objectives. One method to formulate a multi-objective optimization problem is to use a weighted sum approach which can be expressed as:

$$Maximize\ f(x) = \sum_{i=1}^{n} Щ_i \gamma_i(x)$$ [17]

Where:

$f(x)$ is the overall objective function.

$\gamma_i(x)$ represents the individual objective functions.

$Щ_i$ are the weights assigned to each objective function, reflecting their relative importance.

n is the number of objectives.

For combining two or more -objective optimization problem (Pandian et al., 2024).

, the equation can be written as:

$$Maximize\ f(x) = Щ_1\gamma_1(x) + Щ_2\gamma_2(x)$$ [18]

In MOO, it's often useful to normalize the objective functions to ensure they are on a comparable scale:

Where:

$$\hat{f}_i(z) = f_i(z) - f_i max - f_i min$$ [19]

$\hat{f}_i(z)$ is the normalized objective function.

$f_i(z)$ is the original objective function.

$f_i min$ is the minimum value of the objective function.

$f_i max$ is the maximum value of the objective function.

Pareto Dominance

A solution z_1 is said to dominate another solution z_2 if:

∀i ∈ {1, 2…...,n}, $f_i(z_1) \leq, f_i(z_2)$ $and\ \exists i \in \{1,2,\ldots,n\}\ _i(z_1) \leq \}, f_i(z_2)$

Where:

n is the number of objective functions.

$f_i(z_1)$ and $f_i(z_2)$ are the values of the i-th objective function for solutions z_1 and z_2 respectively.

ε-Constraint Method

Another approach is the ε-constraint method, which converts a multi-objective optimization problem into a single-objective problem by treating one objective as the primary goal and the others as constraints:

$$Maximize \quad f_i(z)$$

Subject to $f_i(z) \leq \epsilon_{i,}\ i = 1,2,3 \ldots \ldots n$

2.12.1 Hybrid Metaheuristic algorithms

Hybrid Metaheuristic algorithms combine two or more optimization techniques to leverage their strengths and mitigate their weaknesses. These algorithms are designed to improve search capabilities, convergence speed, and solution accuracy. Combination of Techniques: Hybrid algorithms integrate different metaheuristic approaches, such as Genetic Algorithms (GA) with Simulated Annealing (SA) or Particle Swarm Optimization (PSO) with Ant Colony Optimization (ACO).

Enhanced Performance: By combining techniques, hybrid algorithms can achieve better performance in terms of exploration and exploitation, leading to more robust and efficient solutions. Hybrid metaheuristics are used in various fields, including engineering, logistics, scheduling, and machine learning (Ting et al., 2014). Basic hybrid metaheuristic algorithm is shown in figure 2.7.

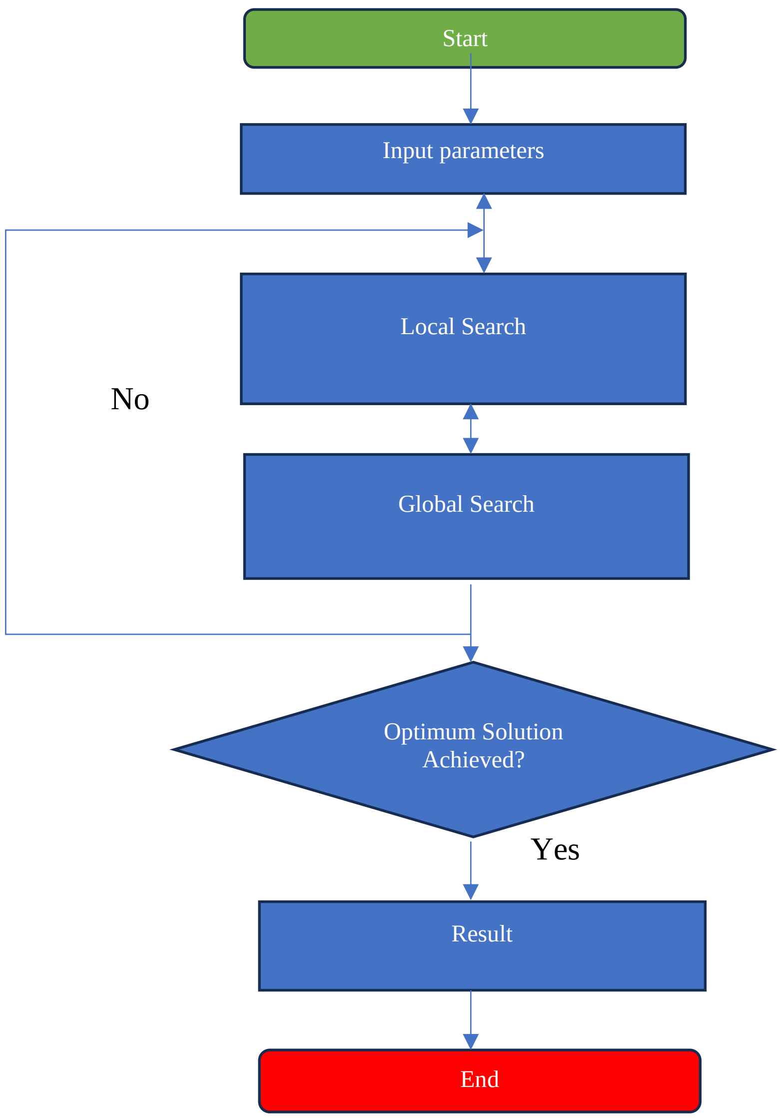

Figure 2.7 Basic hybrid Metaheuristic algorithm

2.12.2 Deep learning and Machine learning

Fuel cell development and optimization depend heavily on effective performance, service life, and fault detection evaluation techniques. By covering popular machine learning approaches such neural networks, support vector machines, and random forests as well as intelligent optimization methods, this research highlights the significance and current status of machine learning applications in fuel cells (Smith et al., 2010, Lee et al., 2020). These techniques train surrogate models using data from trials and physical models.

Machine learning-trained data driven surrogate models make accurate predictions in less than a second, with accuracy on par with physical models and experimental data. Compared to actual CFD models and tests, which might take hours, this drastically cuts down on the amount of time needed to obtain data. Therefore, machine learning reduces workload and expenses by improving computing efficiency (Zhang et al., 2018, Chen et al., 2022).

When properly chosen and trained, machine learning approaches accurately solve nonlinear problems and correlate well with physical models and experimental data, making them suitable for use in fuel cell performance prediction, service life estimation, and defect diagnostics. A number of optimization objectives for design and execution parameters have been successfully attained with high accuracy and efficiency by combining machine learning models with intelligent optimization algorithms (Kim et al., 2021).

Real-Time Optimization:

Real-Time Optimization in PEMFCs involves dynamically adjusting the operating parameters to maximize performance and efficiency in real-time. This is crucial for applications where conditions change rapidly, such as in automotive or portable power systems. Real-time optimization continuously monitors and adjusts parameters like temperature, pressure, and humidity to ensure optimal performance. Common techniques include model predictive control (MPC), adaptive control, and machine learning algorithms. Real-time optimization is used in various PEMFC applications, including hybrid electric vehicles and portable power systems (Karthikeyan et al., 2024).

Here, the general equation often used in the optimization of PEM fuel-cell operating parameters can be defined as follows.

$$Maximize\ f(x) = \in_{PEMFC}{}^{(x)}.P\ _{output}(x)\ - C(x) \quad [20]$$

Where:

$\in_{PEMFC}{}^{(x)}$ is the efficiency of the PEM fuel cell as a function of operating parameters x.

$P\ _{output}(x)$ is the output power of the PEM fuel cell as a function of operating parameters x.

$C(x)$ is the cost function associated with the operating parameters x.

Real-time optimization can be formulated as a generalized equation, often involving a linear complementarity problem (LCP) to track the solution manifold. The equation can be expressed as (Faria et al., 2023):

$$z\ such\ that\colon\ 0 = F(z,t) + G(z,t)u\ and\ z \geq 0, u \geq 0, z\ ^{t}u = 0 \quad [21]$$

$F(z,t)$ represents a function dependent on the variable x and time t.

$G(z,t)$ represents another function influenced by x and t, with u being a control variable.

$z \geq 0\ and\ u \geq 0$,ensure that the variables are non-negative.

The $z\ ^{t}u$ = 0 (where $z\ ^{t}$ is the transpose of z) enforces that either z or u must be zero in every entry, representing a complementarity condition.

Above equation is used to ensure that the system adheres to both equality and inequality constraints, often found in economic and engineering optimization problems.

2.13 Challenges

2.13.1 Computational complexity

Computational Complexity in the context of metaheuristic algorithms refers to the resources required (primarily time and memory) to perform the optimization, particularly as the size of the problem increases. Many metaheuristic algorithms, such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Ant Colony Optimization (ACO), can become computationally expensive for large-scale problems due to the following reasons:

Factors contributing to Computational complexity:

High Dimensionality: Large-scale problems often have many variables, increasing the search space exponentially.

Iteration Counts: Metaheuristic algorithms typically require many iterations to converge to an optimal or near-optimal solution.

Evaluation Costs: Each iteration involves evaluating a population of potential solutions, which can be computationally intensive.

Algorithm Complexity: The inherent complexity of the algorithm's operations (e.g., selection, crossover, and alteration in GA) can add to the computational load.

Mitigation Strategies:

Parallel Processing: Distributing the computational load across multiple processors can significantly reduce execution time.

Hybrid Approaches: Combining metaheuristic algorithms with other optimization techniques to leverage their strengths and improve efficiency.

Heuristic-based Reduction: Using heuristics to reduce the search space or simplify the problem.

Adaptive Algorithms: Designing algorithms that adapt their search strategy based on the problem characteristics and progress (Blum et al., 2003).

2.14 Summary of literature review and objective of the proposed work

Based on the above literature review, it can be summarized that the optimization and control of PEMFC is very much essential for its application in dynamic mode. Moreover, it is also found that the several metaheuristic algorithms like PSO, BCO, ACO, SFLA, and DHOA and their application in optimization in PEMFCs have been reported by many researchers and scientists.

It is found that the metaheuristic algorithms are most important algorithms which can be used in PEMFC along with the ANN optimization techniques. In addition, the metaheuristic algorithms offer unique control strategies to minimize the various losses associated in the PEMFC polarization curve. Therefore, for this study, all the various metaheuristic algorithms namely PSO, BCO, ACO, SFLA, and DHOA have been applied successfully in the PEMFC optimization and discussed in this study. It uses the common principles in their inspiration from natural behaviours and processes but their specific mechanisms and applications can vary widely. Understanding the performance characteristics of each metaheuristic algorithm is crucial for selecting the appropriate algorithm for a given optimization problem. Many scientific reports have been discussed about the optimization techniques on the controlling parameter for PEMFC using metaheuristic algorithm. The controlling parameters remain active only during the phase transition of the electro chemicals processes. It is evident that it is very difficult in controlling parameter for PEMFC operation by manual methods. Therefore, online optimization is very much essential to achieve the PEMFC desired performance in dynamic states. To overcome these types of problems, in this work many control strategies have been proposed based on the above literature review and the same are discussed in the subsequent sections.

In the chapter 3, the PEMFC performance optimization is discussed using Artificial Neural Network (ANN) model. It can be noted that the ANN is he basic building block of metahurestic algorithm. This artificial neural network model in PEMFC has been explored and shown to be very useful in comprehending fuel cell optimization with hidden parameters at that level that are only available during electrochemical transition. The various mathematical tools are used for the optimization of PEMFC using artificial neural network. In case of optimization using ANN, the most important input PEMFC operating parameters like stack temperature, pressure, relative humidity, partial pressure of hydrogen, partition pressure of oxygen, anode stoichiometry, and cathode stoichiometry have been considered for the optimization and control cell performance. The ANN model is used for the incorporation of novel metahuristic algorithm and discussed in the chapter 3 and 4, respectively.

In chapter 4, a novel optimization technique called Dynamic Ant Colony Optimization (DACO) was proposed. Unlike ACO, DACO considers food particles as dynamic entities, increasing accessibility and improving accuracy. DACO has been tested using ten different benchmark functions and compared against other optimization algorithms, including GA, ABC, ACO, and GWOCO. Comparative analysis of sum squared error (SSE) and computational time for PEMFC parameter optimization is presented for the developed algorithm DACO and compare with others.

In chapter 5, another novel optimization technique developed which is known as Wild Chimpanzee Hunting Optimization Algorithm (WCHO) and applied in PEMFC optimization using ANN model. This algorithm follows a similar working principle to DACO but incorporates additional features such as time of flight and range of oscillation to refine results. To validate the PEMFC model with WCHO algorithm, ten benchmark functions have been considered for their performance analysis. In result section WCHO compared with other optimization algorithms, including GA, ABC, ACO, GWOCO and previous developed algorithm DACO. Comparative analysis with the two newly developed algorithms of DACO and WCHO has been carried out.

In chapter 6, this DACO optimization algorithm is used in optimization of PID controller parameters. This chapter discusses how the performance of PEMFC controller optimization is improved by controlling a DC/DC converter using various methods, including conventional PID, DACO (Dynamic Ant Colony Optimization)-based PID, DACO-based FOPID, PSO-based PID, PSO-based FOPID, BEE Colony-based PID, and BEE Colony-based FOPID controllers. A Simulink model of a PEMFC is created with controllers and dual inputs for oxygen airflow and hydrogen flow. The suggested methods have been compared with the system-generated results and a conventional PID controller. The optimization algorithms DACO, BEE Colony, and PSO were used with fitness functions IAE, ISTE, and ITAE. Performance have been evaluated based on rising time (TS), maximum overshoot (MP%), and fitness function value. The suggested techniques have been used to optimize the PID and FOPID controller parameters, and outcomes are analysed against conventional PID methods, identifying the optimal values empirically.

Finally in chapter 7, concluding remarks and future scope of this thesis has been carried out.

CHAPTER 3

Modelling and Control of a PEM fuel cell performance using Artificial Neural Networks to maximize the real time efficiency

Multi objective optimization using artificial neural network to maximize the power output of PEMFCs. *Indian Chemical Engineer, 66*(4),323–336.

3.1 Introduction

Fuel cells (FCs) are potential alternative energy sources with positive environmental impacts, including power plants, home applications, and commercial energy generation. PEMFCs, which operate at low temperatures, offer high energy density and safe operation. They are gaining attention in the automobile industry due to their low operating temperature and outstanding performance. Figure 3.1 depicts schematic view of an operational PEMFC. In order to reduce costs and optimize performance, mathematical models and simulations are needed, with artificial neural networks being effective tools (Chang et al., 2011, Chang et al., 2000, Krishnadass et al., 2006, Li et al., 2005).

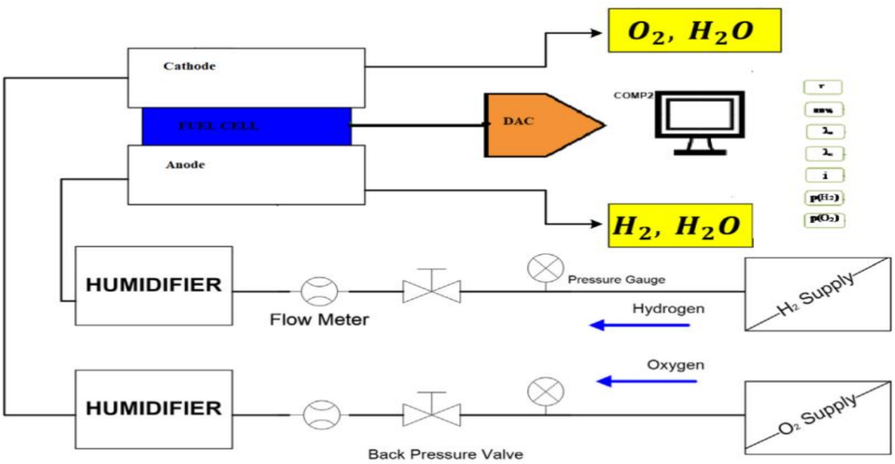

Figure 3.1 Schematic diagram of fuel cell system

Zhang et al. (2008) created a model for water management with Recurrent Neural Network optimization (RNN). The authors also provided a control mechanism of the model and for model implementation, the MATLAB and SIMULINK environments were utilized. Simulations demonstrated that by using this method, variations in the quantity of water present in the cathode may be reduced, hence prolonging the operational lifespan of the PEMFC stack. Fault tolerance control was allowed by Sisworahardjo et al. (2010) in a separate examination. An abundance of scholarly articles has utilized a variety of methods to improve the performance of a solitary PEMFC (Barbir et al., 2006). In order to improve the performance polarization curve while applying EES, Salva et al., (2016) conducted optimization study (Solving the engineering equation). An optimization model might potentially boost the power density of a PEMFC, as suggested by Jemeı et al., (2003) a simplex search approach and simulated annealing were employed to solve the fuel cell numerical model. By applying the Taguchi method, Kaytakoglu and Akyalcin determined the optimal PEMFC operating conditions for greatest power density. The study utilizes an Artificial Neural Network to optimize power output using (Salva et al., 2016) analytical one-dimensional model as a dataset. The model uses an artificial neural network (ANN) with Levenberg-Marquardt and gradient decent algorithms, validating PEMFC performance under various working conditions including temperature, relative humidity in the cathode and anode, and cathode and anode stoichiometry using MATLAB (Sharma et al., 2017). The study focuses on the development of a neural network, utilizing MATLAB for automatic training, accuracy assessment, and prediction or classification using the new dataset.

3.2 Artificial Neural Network model

An Artificial Neural Network (ANN) is a system of neurons that can learn and construct non-linear mappings using input and output data. It provides a solution for modelling complex systems without variable relationships (Saengrung et al., 2007, Bhagavatula et al., 2012). Two main topologies comprise neural networks: feed-forward networks and recurrent networks. Feed-forward networks use hidden layers between input nodes and output layers to convert output from one layer into input from the one below. The Multi-Layer Perceptron (MLP) type is a common choice in PEMFC modelling. The MLP comprises three divisions: input, output, and intermediate or hidden layer, each performing a biased weighted sum of inputs and sending it to a transfer function. The output is determined by the activation level of this transfer function. Network weights are established using training techniques to minimize discrepancies between computed output and experimental results. Two strategies are commonly employed by neural networks: supervised learning and unsupervised learning with back-propagation (Peng et al., 2017) being the most commonly employed supervised training algorithm.

I. A set of examples is compiled for the network training. Each item contains the network's inputs and the appropriate solution for the desired network output.

II. The network's output is computed.

III. The difference between the target vector of the learning pair and the network's output is identified.

IV. The network weights are modified to reduce inaccuracies.

V. Steps 1 to 4 are repeated for each vector in the instruction category to reduce the error for the entire category to a satisfactory level.

The training procedure employed gradient descent and Levenberg-Marquardt of Artificial Neural Network, genetically optimizing the network's inputs, weights, and hidden layer processing components. The network's weights are adjusted through the learning algorithm, which completes an epoch after receiving the entire data set and considers the training duration:

The network is trained multiple times (or "epoch"), with the process repeated if the results are not satisfactory (Li et al., 2020).

The network undergoes training to improve its network performance, which is evaluated after each round of data, using either a training series or cross-validation data series. Both strategies mentioned can be combined as graduation criteria.

Before approaching to ANN model some of the parameters as constant have been considered. Channel Width, Channel depth, Channel length, Rib width, Cell width, GDL thickness, CL thickness, Membrane thickness are considered as constant as mentioned in Table 3.1.

The model has been developed by using the dataset of abovementioned input parameters. operating temperature (T), partial pressure of hydrogen (P_{H_2}), partial pressure of oxygen (P_{H_2}) relative humidity of anode (RH_a), relative humidity of cathode (RH_c) anode stoichiometry, cathode stoichiometry are the input data. Output voltage of fuel cell is considered as output variable. The output power is derived from the known voltage and current (Lu et al., 2024).

Neural network performance is often assessed using cross-validation to predict outcomes and avoid overfitting. The genetic approach (Salimi et al., 2020) is a valuable learning tool for training MLP, utilizing genetic algorithms to simulate natural development progression.

Table 3.1 Model geometric parameters during ANN modelling

Parameters	**Value (mm)**
Channel width	1.0
Channel depth	1.0
Channel length	40.0
Rib width	1.0
Cell width	2.0
GDL thickness	0.3
CL thickness	0.0129
Membrane thickness	0.108

The most beneficial choice is a chromosomal population, where the number of chromosomes is evenly distributed and randomly allocated. The solution's value is assessed using a fitness function (Wang et al., 2021, Na et al., 2007), and the number of generations is established through multiple iterations. Four approaches are often utilized in the application of genetic algorithms.

I. The neural network is awarded the best possible input.

II. The parameters of neural networks are optimized.

III. Actual weights for the network are trained.

IV. Modify the neural network's architectural design.

3.3 Mathematical expression of fuel cell

Nomenclature

V_{OFC}	Fuel Cell Open voltage
E_O	Open circuit voltage of one cell
R	Universal gas constant
F	Faraday constant
T	Stack temperature
$W_{H_2O_A}^{membrane}$	Water vapour from anode side
J_1 and J_2	Combine matrix

$$Anode \rightarrow 2H_2 \rightarrow 4H^+ + \{4e^-\} \qquad [22]$$

Water is generated as a by-product of the reaction between oxygen and hydrogen ions at the cathode. The fuel cell emits water. The cathodic reduction reaction is:

$$Cathode \rightarrow O_2 + \{4e^-\} + \{4H^+\} \rightarrow 2H_2O \qquad [23]$$

The output voltage of a PEMFC is primarily determined by operating conditions such as stack temperature, partial pressure, humidity, and mass flow rate of hydrogen and oxygen, as well as load variation (Ang et al., 2010). The polarization curve is often used to explain the static features associated with a fuel cell. The output voltage decreases nonlinearly as the current density increases. The open circuit voltage of a PEM Fuel cell is as follows:

$$V_{O,FC} = n_S.E_0{}^{Cell} + \frac{n_S RT}{2F} ln\left[\frac{P_{H_2}.(P_{O_2})^{0.5}}{P_{H_2O}}\right] \quad [24]$$

In this equation, P stands for partial pressure of the relevant elements, V for fuel cell voltage, E open-circuit voltage of one cell, R for the universal gas constant, T for stack temperature, n for the number of fuel cells, and F for the faraday constant. Now, the fuel cell meets three distinct types of losses when it is connected to supply electrical energy for any application.

- ***Activation losses:*** These losses occur due to the sluggish nature of electrode kinematics at lower current density.
- ***Ohmic losses:*** These are the losses that occur most commonly in electrical circuits. Nevertheless, this occurs in a fuel cell due to the resistive properties of the cathode and anode.
- ***Concentration losses:*** The observed occurrences are explained to concentration gradients caused by reactance on the electrode surface.

So, the real output voltage of the fuel cell is adjusted to account for the aforementioned losses.

$$V_{fc} = V_{O,FC} - n_S.(V_{loss}{}^{Act} + V_{loss}{}^{O} + V_{loss}{}^{Conc}) \quad [25]$$

$$V_{loss}{}^{Act} = a_0 + T[a + b\, ln(I)] \quad [26]$$

$$V_{loss}{}^{O} = IR_{ohm} \quad [27]$$

$$V_{loss}{}^{Conc} = -\frac{RT}{eF} ln\left(1 - \frac{I}{I_L}\right) \quad [28]$$

The difference between oxygen and hydrogen flowing inside and outside the cathode and anode determines the net mole flow rate of oxygen and hydrogen. As the variable load fluctuates, the flow rates do not respond instantaneously.

$$\frac{d(M_{O_2})_{net}}{dt} = \frac{1}{\lambda_C}\left(\frac{I}{4F} - (M_{O_2})_{net}\right) \qquad [29]$$

$$\frac{d(M_{H_2})_{net}}{dt} = \frac{1}{\lambda_A}\left(\frac{I}{2F} - (M_{H_2})_{net}\right) \qquad [30]$$

The equation of PEMFC reveals that fuel cell output voltage is a dependent variable. All the above-mentioned input parameters have large impact on fuel cell power generation. By using the ANN, it has been tried to developed a model where output voltage can be predicted.

3.4 Optimization of ANN modelling using MATLAB

Preprocess data: Preparing the raw data for input into the neural network, this module applies a variety of preprocessing techniques.

Tag data: The training input, training desired, cross-validation input, cross-validation desired, testing input, and testing desired components of the data are visually tagged using this module.

Create/open network: This module used to form the neural network structure. Connecting different nodes the ANN architecture is completed.

Training the network: Before approaching to the validation, the neural network has been trained. Generally, 70-80 percent data is used for training purpose. If data set is too small, k-fold validation will be carried out.

Tests of the network: Completion of the training testing the neural network will be carried out. 20-30 percent data is used for this method.

Analyze the network: The result has been optimized to obtain best possible solution.

Total 7 no. of parameters have been considered and the number of observations is 27. Here sample data set is attached which is further analyzed for performance prediction of PEM Fuel Cell.

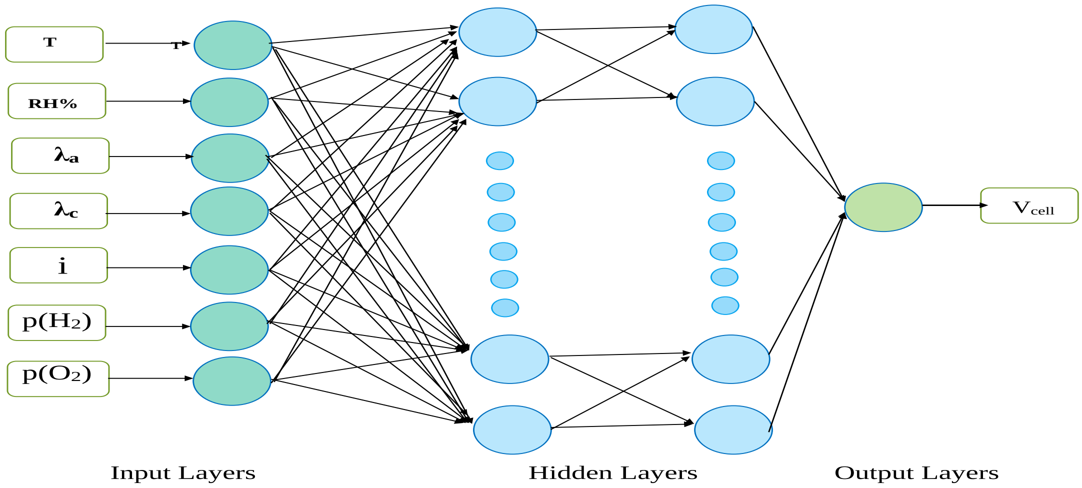

Figure 3.2 Artificial Neural Network model for prediction of PEMFC performance.

In this study, the design process is carried out in MATLAB, where the neural network's MLP model is developed. Figure 3.2 illustrates the network topology. The network depicted in this figure consists of one input layer, one hidden layer, and one output layer. The network inputs consist of operating temperature (T), partial pressure of hydrogen (P_{H_2}), partial pressure of oxygen (P_{O_2}) relative humidity of anode (RH_a), relative humidity of cathode (RH_c), anode stoichiometry (λ_A), cathode stoichiometry (λ_C). The network's output is the voltage. Table 3.2 displays the network input parameters' ranges. The sigmoid activation function is utilized for both the hidden and output layers.

The ratios of reactants (often hydrogen and oxygen) to products (water) at the anode and cathode, respectively, during the electrochemical reaction are commonly referred to as the anode and cathode stoichiometry in a proton exchange membrane (PEM) fuel cell.

Table 3.2 Model physical parameters during ANN modelling

Reference	Input Parameters	Output Parameters
1-3 bar	P_{H_2}	Power
1-3 bar	P_{O_2}	
60,70,80,90 ^oC	T (^oC)	
1.5,3.5,5.5	λ_A	
2-8	λ_C	
80,90,100	RH_a	
80,90,100	RH_c	

Anode Stoichiometry:

At the anode of a PEM fuel cell, hydrogen gas (H_2) is typically oxidized to produce protons (H+) and electrons (e-): $H_2 \rightarrow 2H^+ + 2e^-$

The anode stoichiometry involves ensuring that there is sufficient hydrogen supplied to the anode to maintain the desired rate of reaction without excess, which could lead to inefficiencies or safety concerns.

Cathode Stoichiometry:

At the cathode of a PEM fuel cell, oxygen gas (O_2) is typically reduced by protons and electrons to form water $O_2 + 4H^+ + 4e^- \rightarrow 2H_2O$

The cathode stoichiometry involves ensuring that there is sufficient oxygen supplied to the cathode to facilitate the reduction reaction without causing oxygen starvation, which could decrease cell performance.

3.5 Training of the Neural Network

The training approach used gradient descent and Levenberg-Marquardt of Artificial Neural Network, genetically optimizing the network's inputs, weights, and hidden layer processing components (Ang et al., 2010, Liu et al., 2017). Training module is presented as follows.

• Identifies parameter configurations leading to lowest error.

• Generates initial network population with unique parameter sets.

• Trains and tests each network for fitness.

• Merges and alters favorable network traits for fresh population.

• Inherits optimal network features after recent assessment.

The selected parameters for LM and gradient descent were: Number of Epochs: 1000; Size of Population: 27; Maximum Generations: 100; Maximum Evaluation Time: 60. Mean square error (MSE), the mean absolute error (MAE), and Co-efficient of determination (R^2) between model data and neural network outputs is calculated. The MSE, MAE and co-efficient of determination are defined in equations 31 and 32 as mentioned below:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(X_i - \bar{X})^2 \qquad [31]$$

$$MAE = \frac{\sum_{i=1}^{n}(\bar{X} - X_i)^2}{n} \qquad [32]$$

$\bar{X}$= Predicted Value, X_i= True Value, n= total number of data point

3.6 Results and discussion

Table 3.3 captures the sample experimental data obtained and fed to the ANN. These data are fitted in the ANN network and output results were optimized based on the training data-set.

Table 3.3 Experimental data of seven parameters

No of Observation	P_{H_2}	P_{O_2}	T(ºC)	λ_a	λ_C	RH_a	RH_c
1	1	1	60	1.5	2	80	80
2	1	1	70	1.5	2	90	90
3	1	1	80	1.5	2	100	100
4	1	1	60	3.5	4	80	80
5	1	1	70	3.5	4	90	90
6	1	1	80	3.5	4	100	100
7	1	1	60	5.5	6	80	80
8	1	1	70	5.5	6	90	90
9	1	1	80	5.5	6	100	100
10	2	2	60	3.5	6	80	90
11	2	2	70	3.5	6	90	100
12	2	2	80	3.5	6	100	80
13	2	2	60	5.5	2	80	90
14	2	2	70	5.5	2	90	100
15	2	2	80	5.5	2	100	80
16	2	2	60	1.5	4	80	90
17	2	2	70	1.5	4	90	100
18	2	2	80	1.5	4	100	80
19	3	3	60	5.5	4	80	100
20	3	3	70	5.5	4	90	80
21	3	3	80	5.5	4	100	90
22	3	3	60	1.5	6	80	100
23	3	3	70	1.5	6	90	80
24	3	3	80	1.5	6	100	90
25	3	3	60	3.5	2	80	100
26	3	3	70	3.5	2	90	80
27	3	3	80	3.5	2	100	90

The fitted models were developed using MATLAB Deep Learning Toolbox®, illustrated in Figure 3.3 shows that the ANN model block diagram with 7 inputs terms and 2 output terms (MathWorks, 2022) in the ANN model (Kwan et al., 2018).

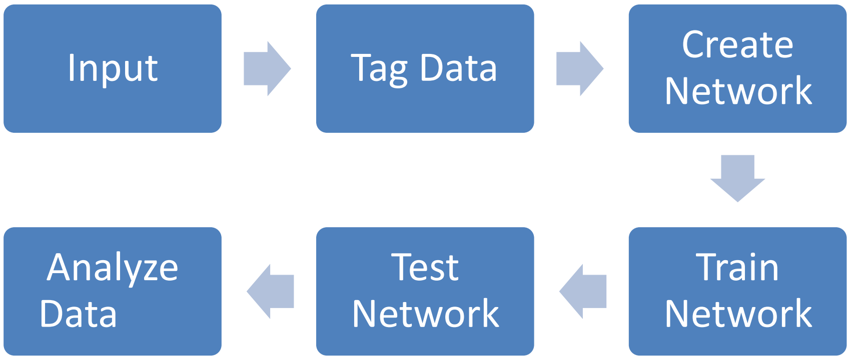

Figure 3.3 Fuel cell-ANN model block diagram representation

The models utilized more than 80% of the 27 data points for training and less than 20% for testing and validation, respectively. Learning algorithms and the number of neurons in the hidden layer were customized for each model to attain the most optimal fit (Salimi et al., 2020, Sohani et al., 2019, Pourkiaei et al., 2016).

Table 3.4 Analysis of stack voltage model

ANN Learning Algorithms	**No of Hidden Neurons**	**Co-efficient of Determination**	**Mean Square Error (V)**	**Mean Absolute Error (MAE)**
LM	1	0.89	$7.1*10^{-4}$	0.08
LM	5	0.94	$4.2*10^{-5}$	0.06
LM	10	0.99	$3.6*10^{-5}$	0.06
LM	15	0.99	$3.6*10^{-5}$	0.06
LM	20	0.99	$3.6*10^{-5}$	0.06
Gradient descent	1	0.9	$5.6*10^{-3}$	0.13
Gradient descent	5	0.93	$2.3*10^{-4}$	0.08
Gradient descent	10	0.98	$2.0*10^{-4}$	0.06
Gradient descent	15	0.98	$3.1*10^{-4}$	0.03
Gradient descent	20	0.98	$2.1*10^{-4}$	0.03

Table 3.4 and table 3.5 compares the coefficient of determination, mean absolute error and mean squared error (MSE) of the stack voltage model for two different learning algorithms.

Table 3.5 Analysis of stack power model

ANN Learning Algorithms	No of Hidden Neurons	Co-efficient of Determination(R^2)	Mean Square Error (V)	Mean Absolute Error (MAE)
LM	1	0.89	$1.1*10^{-3}$	0.08
LM	5	0.94	$4.2*10^{-3}$	0.13
LM	10	0.97	$3.6*10^{-5}$	0.08
LM	15	0.97	$3.6*10^{-5}$	0.08
LM	20	0.97	$3.6*10^{-5}$	0.08
Gradient descent	1	0.9	$5.6*10^{-3}$	0.03
Gradient descent	5	0.93	$2.3*10^{-4}$	0.08
Gradient descent	10	0.96	$2.0*10^{-4}$	0.01
Gradient descent	15	0.96	$3.1*10^{-4}$	0.01
Gradient descent	20	0.96	$2.1*10^{-4}$	0.01

The first column shows the kind of artificial neural network (ANN) learning approach, the second column specifies the selected number of hidden neurons for modelling, and the last three columns provide the results from three statistical analysis tools for the models: coefficient of determination values, MAE (mean absolute error) and MSE (mean squared error). Table 3.5, similar to table 3.4, presents a comparison of the Mean Squared Error (MSE) and coefficient of determination for the stack power model findings across several techniques. From the tables, most models of 5 or higher number of hidden neurons can effectively approximate the PEMFC data well. The hidden layer with less than 5 neurons often results in lower model accuracy compared to a larger number of neurons in the same layer. Furthermore, Gradient Decent and LM algorithm performed consistently based on MSE, MAE and coefficient of determination (Teng et al., 2024).

From the modelling result it has been found out the percentage of contribution in power density of fuel cell. Partial pressure of Hydrogen and partial pressure of oxygen plays maximum role for the generation of output voltage as well as power density. PEMFC performance also depends on temperature variation.

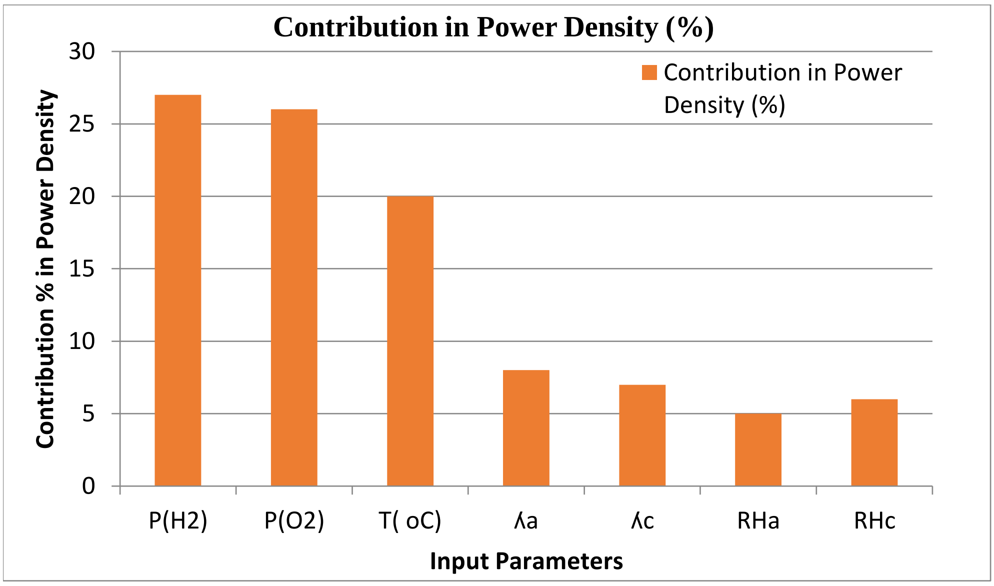

Figure 3.4 ANN result response of different parameter

But relative humidity of anode (RH_a), relative humidity of cathode (RH_c) anode stoichiometry(λ_A), cathode stoichiometry(λ_C) have lesspercentage of contribution to generate the output voltage. This is expressed in a bar chart analysis in Figure 3.4. The polarization curve plotted between voltage vs current density has been shown in Figure 3.5, Figure 3.6, Figure 3.7 and Figure 3.8, keeping one parameter constant at a time.

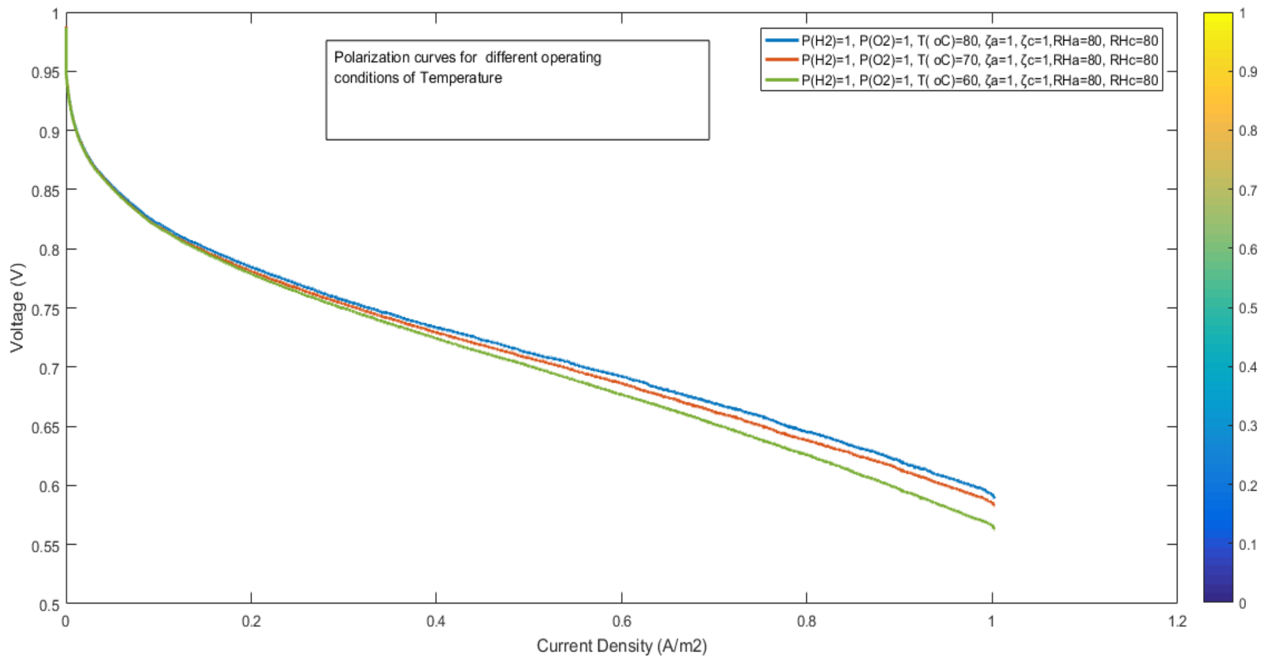

Figure 3.5 Polarization curves for different temperature keeping all other parameters constant

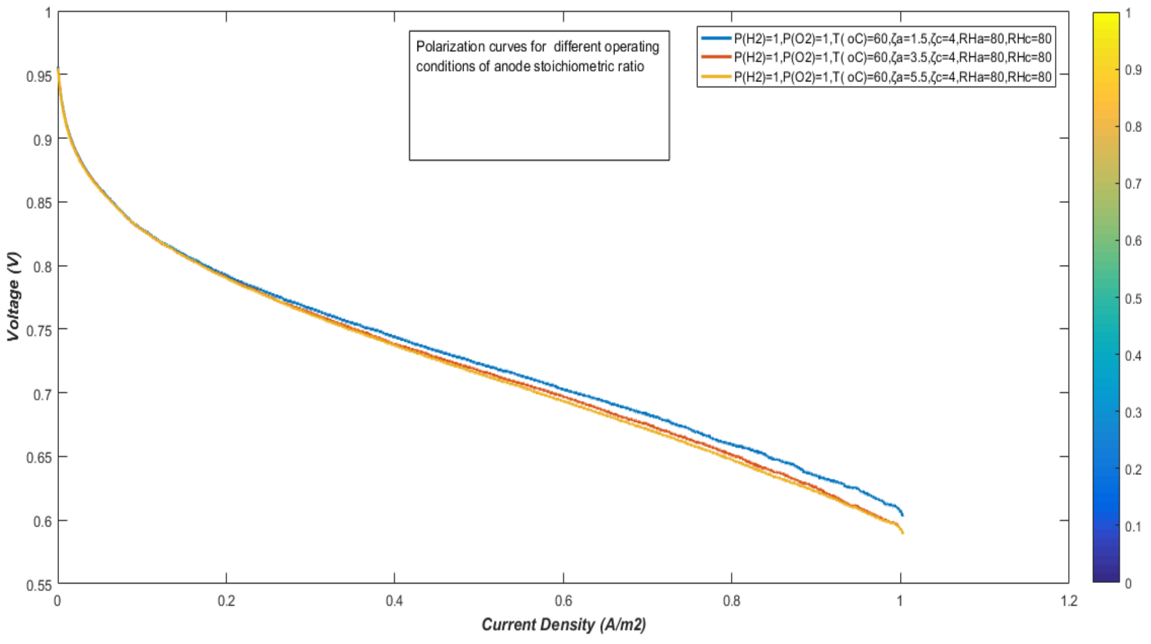

Figure 3.6 Polarization curves for different anode stoichiometric ratio keeping another parameter constant

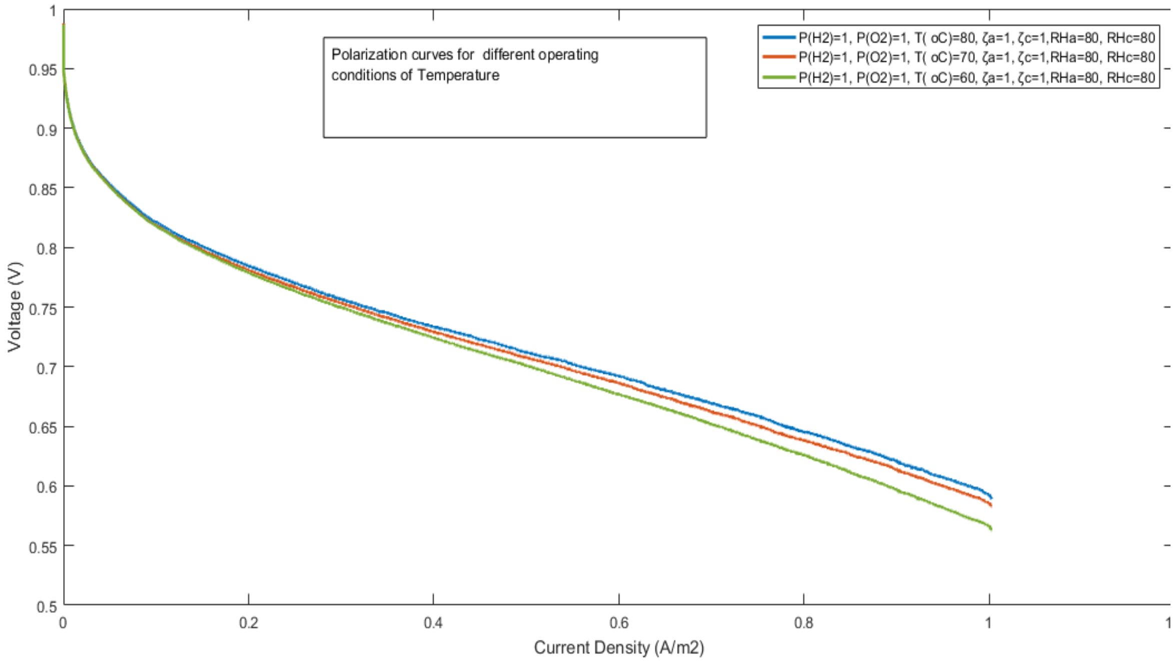

Figure 3.7 Polarization curves for different cathode stoichiometric ratio keeping another parameter constant

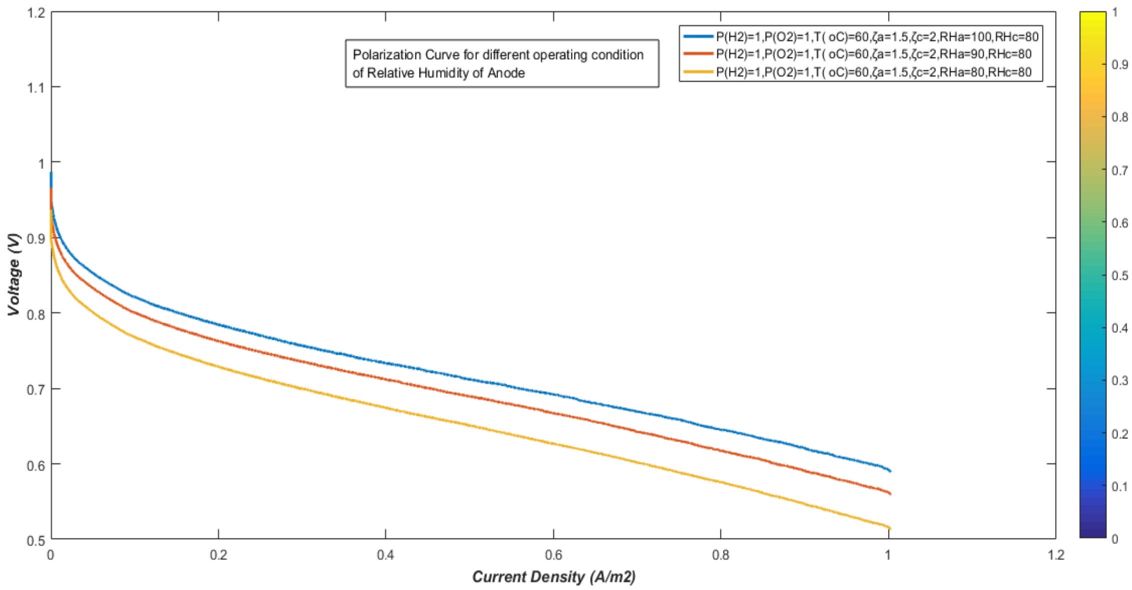

Figure 3.8 Polarization curves for different relative humidity of anode keeping all other parameter constant

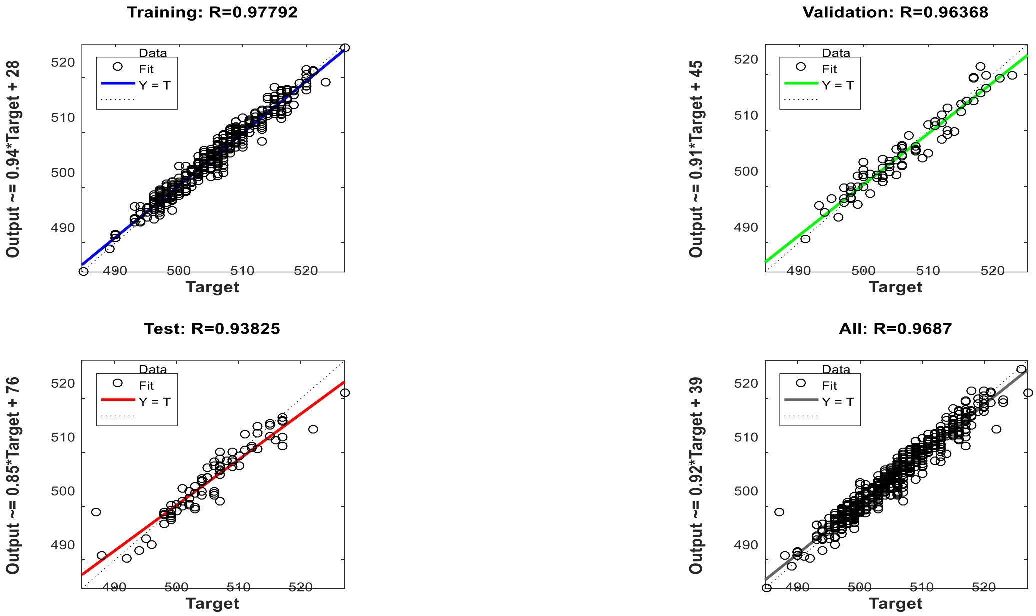

Figure 3.9 Regression of different EPOCH

Regression value of different EPOCH that shown in figure 3.9 is converges to 1 signifies that the experimental value and the predicted ANN values are closes to each other, and the difference of those values are shown in error histogram representation in figure 3.10 also Finally predicted power density is compared with the real time practical fuel cell value at a potential of 0.5 volt. As the number of neurons in hidden layer increased the predicted value of power density becomes much closer to the practical value. The power density obtained from Levenberg Marquardt (LM) back-propagation algorithm and practical data is presented in table 3.6.

Table 3.6 Numerical results obtained at potential of 0.5 V

No of Hidden Neurons	Power density (W/cm^2)	
	Experimental	ANN using ML
1	0.770	0.57
5		0.61
10		0.73
15		0.73
20		0.74

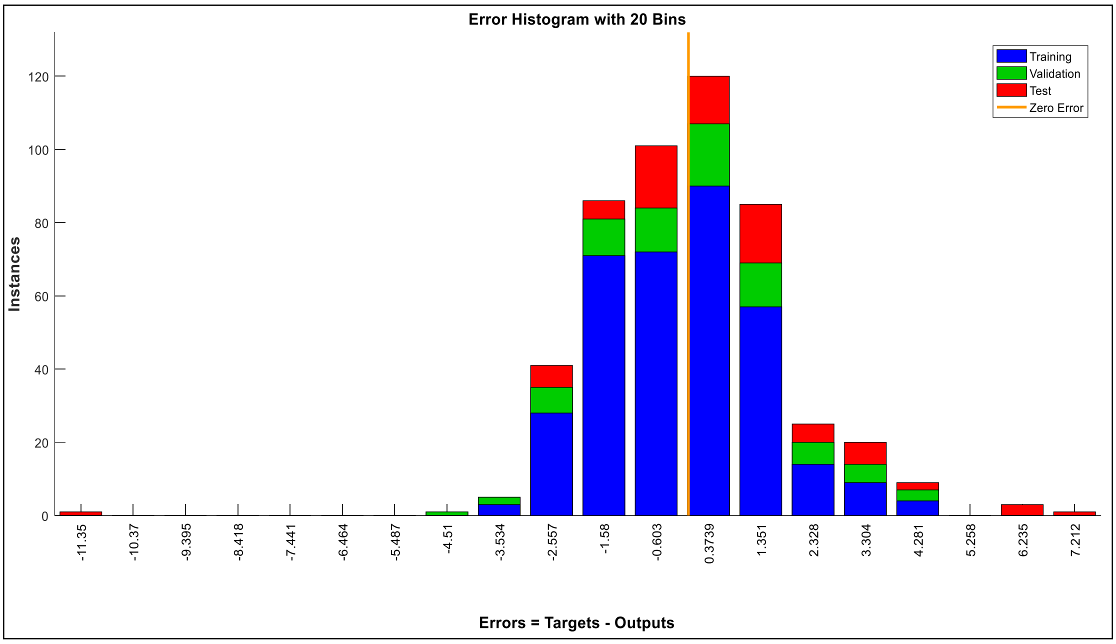

Figure 3.10 Error histogram representation

3.7 Summary on modelling and control of PEMFC using ANN

An essential tool for optimization is modelling. One practical way for simulating nonlinear systems, like PEM fuel cells, is Artificial Neural Networks (ANN) (Zhang et al., 2008, Majdi et al., 2010). The Levenberg-Marquardt learning technique was used to create the multilayer perception network in this study. It is evident that the best learning technique for determining the fuel cell performance parameters is the Levenberg Marquardt (LM) back-propagation algorithm. This study shows that the projected values from the given neural network may be used to estimate the PEM fuel cell's (PEMFC) performance in different scenarios. The PEM fuel cell's working circumstances were the focus of all the models' considerations. Hence, only the ideal operating conditions were used to forecast the power output. Future research will focus on optimizing the PEMFC's performance based on design parameters. Since more compact stacks with fewer cells for a given power output can be created, performance optimization is a crucial strategy for reducing PEMFC costs. The maximum (or lowest) power output as well as the ideal operational circumstances for any current was disclosed by the suggested ANN model, making it possible to anticipate the ideal operating conditions for any current in order to achieve the maximum power output. Another unique aspect of this work is the ANN's application to the analysis of a PEMFC (Sultan et al., 2024, Huang et al., 2024).

In this chapter, optimization of the PEMFC has been studied. Considering all the inactive parameters that are active during electro chemical transition using Artificial Neural Network is quite challenging as the numbers of the parameter increase the complexity of the hidden layers. The numbers of the parameter also increase the poor performance in predicting effective parameters of the fuel cell. This lead to abolish of the Neural Networks in PEMFC fuel cell, when the parameters are larger in numbers. So, the extent of the meta-heuristic algorithms will be explored, which are much more efficient in handling the methods of optimization when the controlling parameter are larger in numbers, as these types of algorithms don’t use the methods of brute forcing the entire combination of controlling parameters to generate optimum output during the electro- chemical transition of the fuel cell. In the next chapter, the effectiveness of the fuel cell will be discussed by one of the many meta-heuristic algorithms. i.e Dynamic Ant Colony Optimization (DACO) which is based on the concept of Ant Colony Optimization method with a feature of handling the lost parameters or dynamically changed parameters which are available during short instant of time only active during electro chemical transition.

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CHAPTER 4

Optimization of PEMFC using Dynamic Ant Colony Optimization Algorithm

Dynamic ant colony optimization algorithm for parameter estimation of PEM fuel cell.

Engineering Research Express, 6(2), 025014.

4.1 Introduction

Proton exchange membrane fuel cells (PEMFCs) are increasingly acknowledged as an appealing option to non-renewable energy sources, owing to their multiple advantages, including sustainability, non-self-discharge, reliability, and lack of pollutants. As a result, fuel cells are utilized in many circumstances. Consequently, it is essential to precisely ascertain the parameters (Singla et al., 2021) of PEMFCs. The simulation, investigation, and design of highly efficient fuel cells rely heavily on accurately assessing their characteristics (Routh et al., 2024). The operation of the fuel cell entails a meticulously regulated chemical process that converts chemical energy into electrical energy. Considering the escalating significance of Proton Exchange Membrane Fuel Cells (PEMFC) and their expanding application in industry, it is essential to develop and enhance a more exact and accurate model to understand the fundamental mechanisms within the fuel cell and improve performance (Mossa et al., 2021). A multitude of endeavours have been undertaken to develop more precise models for the purpose of identifying the functions of PEMFC (Jahromi et al., 2023). The modelling of PEMFC attributes is a critical component of the study, simulation, and development of high-performance and efficient fuel cells. The absence of adequate statistics in the PEMFC model's documentation results, parameter determination (Guarnieri et al., 2016, Askarzadeh et al., 2013) problem is solved using two distinct methodologies (Singla et al., 2021, Liu et al., 2017) such as metaheuristic algorithms and conventional methods. Meta-heuristic algorithms provide complex problem solutions, a global optimal resolution convergence function, and arbitrary initial guesses, while conventional methods are less precise due to their non-linear characteristics. Hybrid stochastic strategies, such as Differential Evolution (DE), Particle Swarm Optimisation (PSO) (Li et al., 2010, Askarzadeh et al., 2010) are employed to obtain a variety of material properties for PEMFC (Abbas et al., 2015, Brest et al., 2007). The Artificial Bee Colony Optimisation (ABC) algorithm can be employed to optimize the PEMFC model parameters (Xiao et al., 2023, Latif et al., 2019) which is based on the foraging behaviours of bees. ABC's objective is to enhance the precision of PEMFC stack models in a steady-state that are suitable for use in electrical engineering applications. GWO, or Grey Wolf Optimizer (Ali et al., 2017, Hassan et al., 2020) is drawing inspiration from the social structure and hunting techniques of grey wolves. GWO simulates the process of seeking for the best answers. The GWOCS algorithm (Hou et al., 2022) is employed to estimate parameters in PEMFC models. Using GWOCS, the parameters of the PEMFC model are adjusted to enhance forecasts and optimize the system. In order to estimate parameters, the Ant Colony Optimisation (ACO) technique (Donati et al., 2020) is implemented in PEMFC. The Ballard Mark V fuel cell has been analysed in this literature, with certain constant input values specified in table 4.1. This literature is intended to illustrate whether the measured voltage may fluctuate if the PEMC parameter undergoes dynamic changes over time. The Dynamic Ant Colony Optimisation (DACO) algorithm must be employed to minimize the sum squared error, which is the discrepancy between the empirical voltage determined by the formula and the actual measured voltage (Vilela et al., 2013). The sum squared error values derived by the DACO algorithm are lower than those of the other optimization algorithms mentioned above.

4.2 Mathematical expression of fuel cell

Nomenclature

$(V_{FC})_O$	Fuel Cell Open voltage
V_{FC}	Actual Fuel Cell output voltage
R_{ohm}	Membrane Resistance
E_C	Open circuit voltage of single cell
R	Universal gas constant

F	Faraday constant
T_S	Stack temp.
Z	No. of Electron Transferred
n_C	No. of Cells

$$Anode \rightarrow 2H_2 \rightarrow 4H^+ + \{4e^-\} \quad [33]$$

Water is generated as a by-product of the reaction between oxygen and hydrogen ions at the cathode. The fuel cell emits water. The cathodic reduction reaction is:

$$Cathode \rightarrow O_2 + \{4e^-\} + \{4H^+\} \rightarrow 2H_2O \quad [34]$$

Many operating variables, such as the partial pressure of H2, the partial pressure of O2, the stack temperature, the mass flow rate of hydrogen and oxygen, humidity, and load fluctuation, significantly influence the output voltage of a Proton Exchange Membrane Fuel Cell (PEMFC) (Routh et al., 2023). The static characteristics of a fuel cell are typically illustrated using the polarization curve. The output voltage experiences a non-linear decline as the current density increases. The open circuit voltage of a PEM fuel cell is as follows:

$$(V_{FC})_O = E_C + \frac{RT_S}{ZF} ln\left[\frac{P_{H_2} \cdot \sqrt{(P_{O_2})}}{P_{H_2O}}\right] \quad [35]$$

In this equation, P stands for partial pressure of the relevant elements, $(V_{FC})_O$ for fuel cell voltage, E_C represents the open-circuit voltage of single cell, R represents the universal gas constant, T_S denotes temperature of the stack, the number of fuel cells denotes by n_c, and F represents the faraday constant. Presently, three distinct categories of losses occur when the fuel cell is being used to provide electrical energy for any application (Talukder et al., 2024).

Activation losses: The slow electrode kinematics at reduced current densities are the cause of these losses, as indicated by ${V_{loss}}^{Act}$

Ohmic losses: These are the losses that occur most frequently in electrical circuits. Nevertheless, it occurs in a fuel cell due to the resistive characteristics of the cathode and anode, which are represented by ${V_{loss}}^{Ohm}$.

Concentration losses: The observed phenomena are attributed to concentration gradients that are the result of reactance on the electrode surface, denoted by ${V_{loss}}^{Conc}$.

The fuel cell's output

voltage is adjusted to account for the losses previously mentioned (Gupta et al., 2021).

$$V_{FC} = (V_{FC})_O - ({V_{loss}}^{Act} + {V_{loss}}^{Ohm} + {V_{loss}}^{Conc}) \quad [36]$$

$${V_{loss}}^{Act} = a_0 + T_S\left[a_1 + a_2\, ln(\,C_{O_2}) + a_3\, ln(\,I)\right] \quad [37]$$

$${V_{loss}}^{Ohm} = IR_{ohm} \quad [38]$$

The difference between the oxygen and hydrogen streaming inside and outside the cathode and anode is the determinant of the net mole flow rate of oxygen and hydrogen. Flow rates are not instantaneously adjusted as the variable load fluctuates. The transit latency can be used to ascertain the net mole flow rate of H_2 and O_2 (Singh et al., 2022).

All the optimizing parameter along with their range have been mentioned in table 4.1.

$$(V_{FC})_O = E_C + \frac{RT_S}{ZF} ln\left[\frac{P_{H_2}.\sqrt{(P_{O_2})}}{P_{H_2O}}\right] \quad [39]$$

Table 4.1. Lower and upper bound range of PEMFC parameters

Parameter	Parametric Range	
	Upper	**Lower**
a_0	$-8.53*10^{-1}$	-1.1996
a_1	$500*10^{-5}$	$100*10^{-5}$
a_2	$9.8*10^{-5}$	$3.6*10^{-5}$
a_3	$-0.954*10^{-4}$	$-2.60*10^{-4}$
R_{Cs} (Ω)	$8*10^{-4}$	$1*10^{-4}$
b (V)	0.5	0.0136
κ	24.00	10.00

At 1 atm and 25 °C or 298.15K

Hydrogen, oxygen, and water partial pressure is given by P_{H_2}, P_{O_2}, P_{H_2O} respectively.

$$P_{H_2} = 0.5\left(RH_{anode} \times P_{H_2O}\right)\left[\left(exp\left(\frac{1.635\left(\frac{I}{A}\right)}{T_S^{1.334}}\right) \times \frac{\left(RH_{anode} \times P_{H_2O}\right)}{P_{anode}}\right)^{-1} - 1\right] \quad [40]$$

Where RH_{anode} and $RH_{cathode}$ represent the relative humidity of the vapor surrounding the anode and cathode sides of the fuel cell, respectively, and I represent the flow of current in a fuel cell, while a cross-sectional area of the membrane is denoted.

$$P_{O_2} = \left(RH_{cathode} \times P_{H_2O}\right)\left[\left(exp\left(\frac{4.192\left(\frac{I}{A}\right)}{T_S^{1.334}}\right) \times \frac{\left(RH_{anode} \times P_{H_2O}\right)}{P_{cathode}}\right)^{-1} - 1\right] \quad [41]$$

$$P_{H_2O} = 2.95 \times 10^{-2}(T_S - 273.15) - 9.18 \times 10^{-5}(T_S - 273.15)^2 + 1.44 \times 10^{-2}(T_S - 273.15)^2 - 2.18 \quad [42]$$

$$(V_{FC})_O = 1.3 - 8.5 \times 10^{-4}(T_S - 298.15) + 4.3085 \times 10^{-5} T_S * (ln(P_{H_2}) + ln\left(\sqrt{P_{O_2}}\right)) \quad [43]$$

$$V_{loss}{}^{Act} = a_0 + T_S[a_1 + a_2\, ln(\, C_{O\,2}) + a_3\, ln(\, I)] \quad [44]$$

$$C_{O_2} = \frac{P_{O_2}}{5.08 \times 10^6 \exp^{\left(\frac{-498}{T_S}\right)}} \quad [45]$$

$$V_{loss}{}^{O} = IR_{ohm} = I(R_{MS} + R_{CS}) \quad [46]$$

R_{MS} is Membrane Resistance, and R_{CS} is Contact resistance

$R_{MS} = \frac{\rho_M l}{A}$, where ρ_M denotes Resistivity of membrane

$$\rho_M = \frac{181.6\left(1 + 0.03\left(\frac{I}{A}\right) + 0.0062\left(\frac{T_S}{303}\right)\left(\frac{I}{A}\right)^{2.5}\right)}{\left(\kappa - 0.634 - 3\left(\frac{I}{A}\right)\right) exp\left(418\left(\frac{T_S - 303}{T_S}\right)\right)} \quad [47]$$

κ stands for adjustable Empirical variable

$$V_{\text{concentration}} = -b\, ln\left(I - \frac{\frac{I}{A}}{\frac{I_{max}}{A}}\right), \quad [48]$$

if φ represents current density of single PEMFC and $\varphi_{\max}$ is maximum of that, then above equation can be expressed as

$$V_{\text{concentration}} = -b\, ln\left(I - \frac{\varphi}{\varphi_{\max}}\right) \quad [49]$$

$b = \frac{RT_S}{z\alpha F}$,

where *b* is parametric constant.

$$V_{\text{stack}} = n_c \cdot (V_{FC}) \quad [50]$$

$$V_{\text{stack}} = n_c((V_{FC})_O - (V_{loss}{}^{Act} + V_{loss}{}^{Ohm} + V_{loss}{}^{Conc})) \quad [51]$$

Here in this literature optimization function is defined below which to minimize the sum squared error.

$$MIN(F = \sum_{i=1}^{N} (V_{\text{measured}} - V_{calculated})^2) \quad [52]$$

4.3 Optimization method of Dynamic Ant Colony algorithm

This research introduces a novel optimization algorithm known as the Dynamic Ant Colony Optimization Algorithm (DACO). It incorporates the dynamic movement of food particles and expands upon the principles of Ant Colony Optimization (ACO) (Fidanova et al., 2006, Alaya et al., 2007, Dong et al., 2016).

The "ant colony" algorithm is derived from the concept of collective intelligence, which is demonstrated by the behaviour of ants in efficiently locating the best pathways for obtaining food. Each iteration of the algorithm corresponds to a specific ant constructing its own route, representing the order fulfilment sequence. Every ant must create a solution by navigating the graph. To choose next node the ant will consider the degree of the node which is donated by δ(v), higher the degree of the node the less likely the ant will choose that path. At each step the ant movement will be from node i to j. Thus, the ant will create an optimum solution with each iteration which will avoid a node with higher degree. For ant K, P^k_{ij} the moving probability from state i to state j depending on the combination of four values, the attractiveness function η_{ij} of the move, the trail level function τ_{ij} move, as computed by some heuristic indicating the prior desirability of that move δ_{ij} , the food probability of existence ∋ indicating how proficient it has been in the past to make that particular move. The trail level is an approach to assess the desirability of the move based on past evidence.

$$P_{ij}^{k} = \frac{(\tau_{ij})^{\alpha} * (\eta_{ij})^{\beta} * \ni * (\delta_{ij})}{\sum_{k=0}^{m} h \in allowedj (\tau_{ih})^{\alpha} * (\eta_{ih})^{\beta} * \ni * (\delta_{ih})} \quad [53]$$

Where, m= maximum no. of distinct path and the quantity of pheromone deposited is denoted by τ_{ij} for traversing from node i to node j, $0 \leq \alpha$ is a parameter used to regulate the influence of the (τ_{ij}), (η_{ij}) desirability of the state traversing ij and $\beta \geq 1$ is a parameter used to regulate the influence of ηij. τij and ηij is used here as the trail level and the attractiveness of for the other possible state traversing.

$\ni$ is the probability of existence of the food item. Which is inversely proportional to the time t. higher the time the $\ni$ will be less. Here the food particle is present at that location only for the specific amount of time t. After time t the food particle may have move or blown away in that instant and probability of the food being traced out after lost or shifted is given by

$$\ni = \frac{\pi r^2 * \theta}{\pi R^2 * 360} \forall \quad [54]$$

Where Θ is the search angle after lost. $0° < \Theta \leq 180°$.

τij is probability of pheromone deposited on the path from state i to state j.

δ_{ij} is the degree of the node j, when the path is considered for choosing for transition state from node i to node j. Figure 4.1 represents the basic diagram of Ant Colony Algorithm with all the mathematical factors involved (Özmen et al., 2020, Skinderowicz et al., 2022).

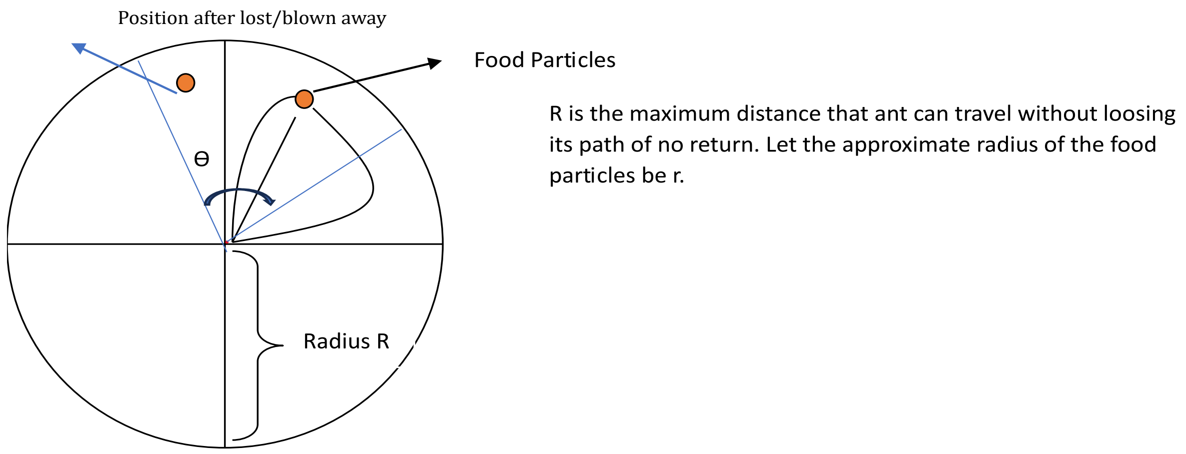

Figure 4.1 Outline diagram of Dynamic Ant Colony algorithm

4.3.1 Route update

The existence of the food particle on any route is inversely proportional to the time t. $\ni = \frac{\pi r^2 * \theta}{\pi R^2 * 360} \forall$

$$\forall = \begin{cases} 1 \text{ when the external agent is absent} \\ 0 \quad \text{otherwise} \end{cases}$$

After time the path has to be reconstructed. With elapsing of the time, the food particle may not be present on that route at that instant of time.

Where τ_{ij} is how much pheromone was release on route for a state change ij, ρ is a coefficient called pheromone evaporation coefficient, m is the number of ants and $\Delta \tau^K_{ij}$, when ∋ is equal to zero, ρ becomes 1, indicating that the ants have ceased to deposit pheromones.

$$\tau_{ij} \leftarrow (1-\rho)\tau_{ij} * (\ni)\tau_{ij} + \sum_{k=0}^{m} \Delta\tau_{ij}^{k} \qquad [55]$$

4.3.2 Pheromone update

The number of trails is frequently adjusted following the completion of all ants' solutions. The number of trails is contingent upon whether the motions were included in "effective" or "obsolete" solutions, and it is increased or decreased accordingly. A paradigmatic example of the principle of global pheromone update is as follows:

$$\tau_{ij} \leftarrow (1-\rho)\tau_{ij} * (\ni)\tau_{ij} + \sum_{k=0}^{m} \Delta\tau_{ij}^{k} \qquad [56]$$

Where τ_{ij} represents the quantity of pheromone that is placed during a transition between states ij, ρ is the pheromone evaporation coefficient, m is the total number of ant present and $\Delta \tau^K_{ij}$ is the amount of the pheromone deposited by the kth ant typically given by

$$\Delta\tau_{ij}^{k} = \begin{cases} \frac{Q}{L_k} if\ ant\ K\ uses\ curve\ ij\ in\ its\ tour. \\ \\ 0\ otherwise \end{cases}$$

Where L_k is the cost function of the kth ant tour (length of the tour) and Q is a constant which denotes probability of existence of the particle at that instant of time. Figure 4.2 represents the flow chart of the dynamic ant colony optimization algorithm.

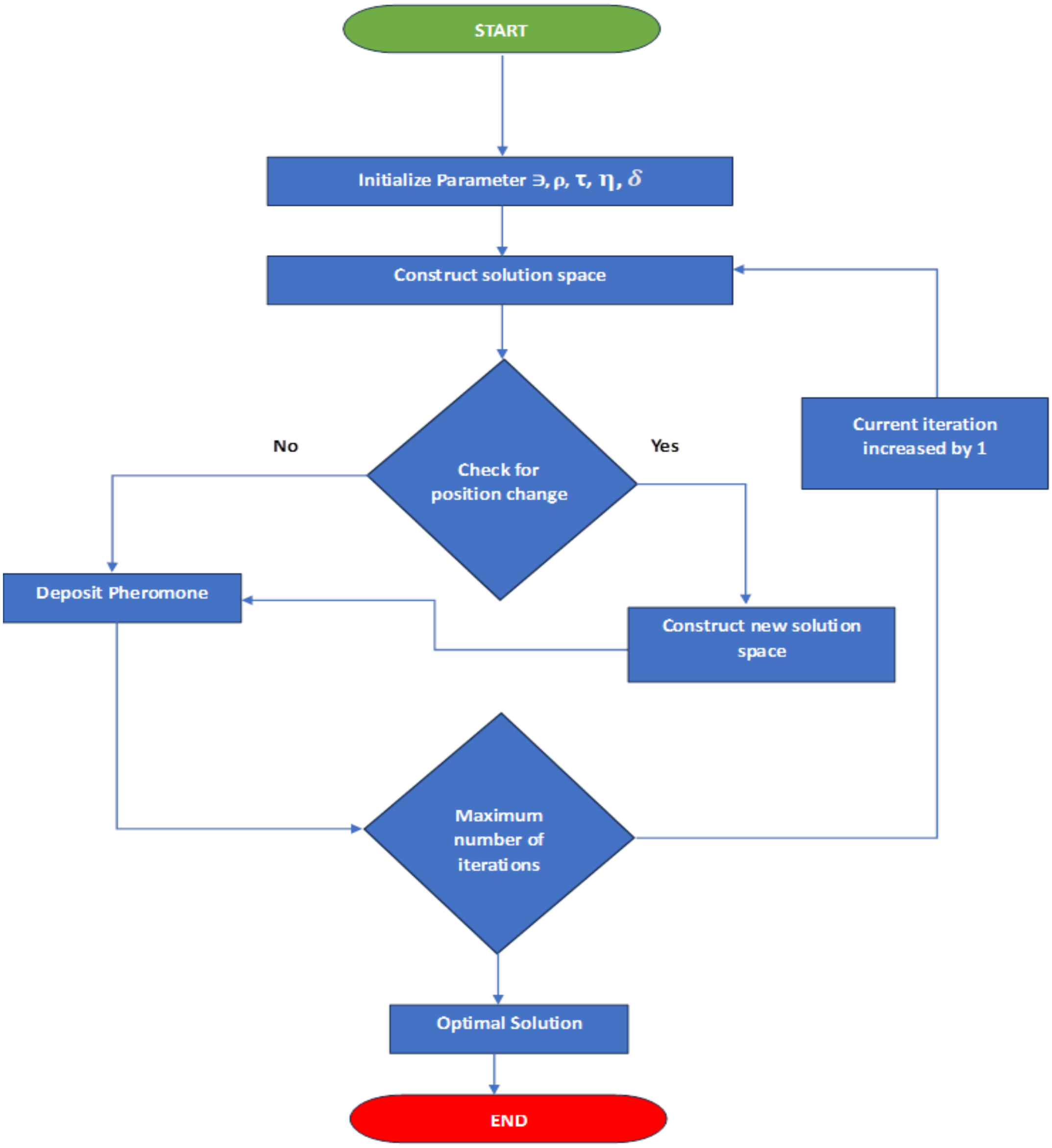

Figure 4.2 Flow chart of the Dynamic Ant Colony Optimization algorithm

4.4 Algorithmic modification of Ant Colony to Dynamic Ant Colony

The DACO algorithm is an extended version or modified version of the ACO. Here before depositing the trail of pheromone the probability of existence of the food particle is taken into consideration. The above scenario is applicable only if the food particle is supposed to be static i.e. not moving. If the food particle is dynamic in nature, then ants that followed the path with the maximum trail of the pheromone deposit may arrive to the place where the food particle was last seen by the k^{th} ant. This will make all the other ants to follow the same path resulting in the maximum deposit of trail of the pheromone in the same path which will result in loss of the resource or cost of transition from nest to food particle.

In case of fuel cell, it can be corelated with the Dynamic position of food particle with the change in parameter value change during the process. For example, one of the parameters as contact resistance (R_{Cs}) has been considered, As the temperature changes, contact resistance will also change as per the law $R_t= R_0(1+\alpha t)$. So, during the process itself any parameters value can be changed due to its inherent properties. In ACO if the parameters value has changed during operation, it was unable to track it. But in case of DACO this has been taken into consideration. The main working principle of the ant colony is it work on concept of choosing the shortest path by way of using pheromone deposit trails. It can be expressed in the form on equation.

$$P_{ij}^{k} = \frac{(\tau_{ij})^{\alpha} * (\eta_{ij})^{\beta}}{\sum_{k=0}^{m} h \in allowedj(\tau_{ih})^{\alpha} * (\eta_{ih})^{\beta}} \quad [57]$$

Where τ_{ij} the quantity of pheromone released for the change of movement from the i to j, $0 \leq \alpha$ s a variable that is used to regulate the influence of the (τ_{ih}) , (η_{ih}) popularity of the state transition ij and $\beta \geq 1$ is a variable, used to regulate the impact of ηij. τij and ηij represent the trail level and the attractiveness of for the other possible state transitions, where τ_{ij} is the volume of pheromone released for the transition from the i to j, $0 \leq \alpha$ is a variable used to control the impact of the (τ_{ih}) , (η_{ih}) is the state transition popularity ij and $\beta \geq 1$ is a parameter used to control the influence of ηij. Trail level and the popularity of the other available state transitions is expressed by τij and ηij respectively.

Here, it can be observed from the figure 4.3 those three ants move from the ant nest in search of the food particles, first one followed the path second one path y and third one path since the path z is shortest the ant will reach the food particles first and return to the nest first and so, the trail of the pheromone will be highest and then next ants will most likely to follow the path z. Four different positions of ant nest and food particle is shown in figure 4.3. The above method of optimization fails to solve the problem when the food particle is dynamic in nature, i.e. by the time ant has reach its nest the food particle has move to next position, or is not available in that case although the trail of the pheromone is highest following the same path may not obtained the food particle.

To overcome such kind of problem in optimization a new method of optimization which is based on the concept of ant colony with added feature is introduced, which can solve the above problem with ease. Here, the modified Ant colony work on the principle of checking the probability of the existence of the food particles after time t, and the branching of the path p.

$$P_{ij}^{k} = \frac{(\tau_{ij})^{\alpha} * (\eta_{ij})^{\beta} * \exists * (\delta\ _{ij})}{\sum_{k=0}^{m} h \in allowedj(\tau_{ih})^{\alpha} * (\eta_{ih})^{\beta} * \exists * (\delta\ _{ih})} \qquad [58]$$

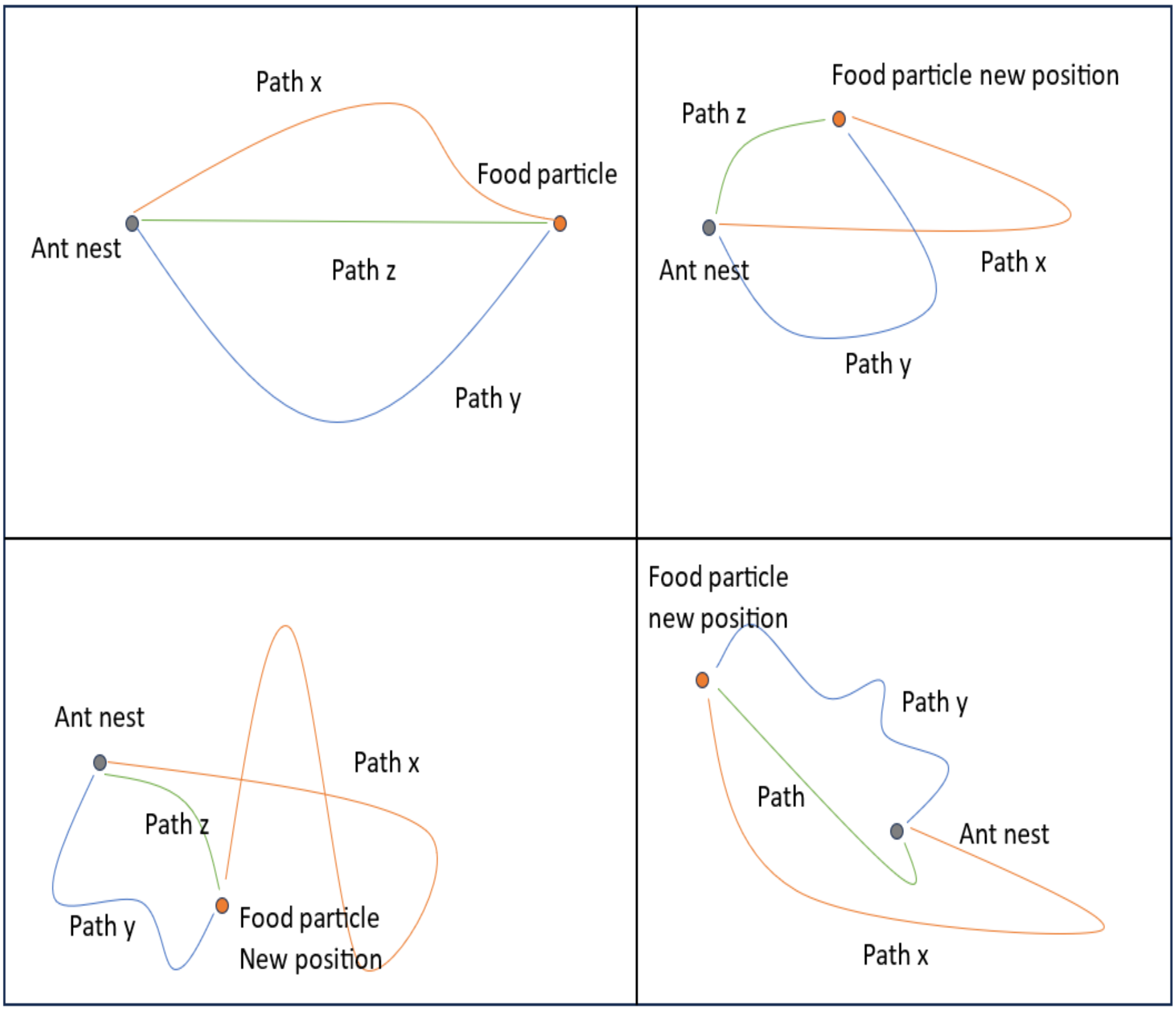

Figure 4.3 Route update in four different positions of Ant Nest and Food Particle

Moment and likelihood of the food being located out after lost or moved is given by $\ni = \frac{\pi r^2 * \theta}{\pi R^2 * 360} \forall$. Where ϴ is the search angle after lost.0° < ϴ ≤ 180°.

By altering the search angle ϴ, one can influence the likelihood of tracing back once the food particle has been lost. The cost is closely correlated with the search angle. The cost increases with the angle.

δ_{ij} is the node j's degree when the path is taken into account while deciding which node to use to move from node i to node j.

$$\delta_{ij} = \left\{ \begin{array}{c} 0 < \delta < x \\ \text{where } x \in N \end{array} \right.$$

$$\forall = \begin{cases} 1 \text{ when the external agent is absent} \\ 0 \quad \text{otherwise} \end{cases}$$

$\forall$ is the random value either 0 or 1. The value of the $\forall$ is 1 when the external agent is 1 otherwise 0. Let the ant has completed its journey from the nest to the food particle following the path z, where the most pheromone trail is present. The probability of choosing the path becomes the most. By the time next ant has reached the destination the food particles are not present at that location due to blown away by external agent (wind, water etc.) or has been stolen by other large ant species or the food particle is living agent. Then by checking the presence of external agent the probability of choosing the same path becomes less likely

Limitation of DACO Algorithm

- DACO is an algorithm designed to solve meta heuristic problems by avoiding brute force methods. This approach is particularly useful when the number of parameters increases, as the algorithm's time complexity increases exponentially. This can result in an unattainable optimal solution within human lifespan. To address this issue, several proposed algorithms have been developed that avoid brute forcing, such as DACO, which is an optimization algorithm that does not use brute force to achieve the optimal solution.

- The DACO optimization algorithm has limitations, including the possibility of solution repetition when parameter size increases. The time complexity of the algorithm is O (Kn^2), where k is the number of ants and n is the number of food particles visited by them. This makes the algorithm less effective for large parameter sizes, as the optimum solution may contain subsets of the sample optimum solution.

- The search angle of food particles and the degree of nodes significantly impact the algorithm's performance. A search angle greater than 180° increases the cost of tracing food particles, leading to poor algorithm performance. The degree of nodes also plays a role, as higher nodes may loop through the same path without being caught during the transition from source to estimation node, with intermediate nodes in between.

Since the algorithm is a revised version of the ACO optimization algorithm, it cannot function effectively if the ACO base pheromone deposition and function is ignored or not taken into consideration. Moreover, as the ant move beyond their point of no return, where the acknowledge of the ant that, whether it has reached to the food particles or not, keeps on waiting state for infinites number of times or till the next successful acknowledgement is received.

4.5 Problem formulation and experimental results

In order to find the best way to estimate the PEMFC parameter, optimization procedures are essential. This research article introduces DACO, a unique approach for reliable and precise parameter estimation in PEMFC (Xu et al., 2019, Mohanty et al., 2022). Utilizing optimization algorithms, predictions are made for the output voltage based on different current density inputs. Furthermore, the evaluation measure used to compare the anticipated output voltage produced from optimization algorithms with the experimental values of the output voltage is the sum of square error (SSE) (Tang et al., 2023). The equation no 20. represents the objective function as $MIN(F = \sum_{i=1}^{N}(V_{\text{measured}} - V_{calculated})^2)$

4.6 Test using benchmark function

Ten test benchmark functions, as shown in table 4.2 have been chosen for this section in order to evaluate the performance of the recently constructed algorithm. The table displays the properties of the features. Multi-modal functions F8 through F10 are different from uni-modal functions F1 through F7. Each function has 30 dimensions.

To assess DACO performance, a number of meta-heuristic algorithms are examined, including PSO, DE, ABC, GWOCS, and ACO. All codes were implemented in MATLABr2022b, and each algorithm was run independently 30 times.

Table 4.2 Test Benchmark Functions used in Proposed Algorithm

Function Name	Function	Min range	Max range	Dimension
$\mathbf{F_1(z) = Sphere}$	$F_1(z) = \sum_{j=1}^{m} z_j^{\ 2}$	-100	100	m = 30
$\mathbf{F_2(z) = Schwefel\ 2.22}$	$F_2(z) = \sum_{j=1}^{m} \lvert z_j \rvert + \prod_{j=1}^{m} \lvert z_j \rvert$	-100	100	m = 30
$\mathbf{F_3(z) = Schwefel\ 1.2}$	$F_3(z) = \sum_{j=1}^{m} \left(\sum_{i=1}^{j} z_i\right)^2$	-100	100	m = 30
$\mathbf{F_4(z) = Schwefel\ 2.21}$	$F_4(z) = \max_j\{\lvert z_j \rvert, 1 \le j \le m\}$	-100	100	m = 30
$\mathbf{F_5 = Rosen\text{-}brock}$	$F_5(z) = \sum_{j=1}^{m} 100\left(z_j + 1 - z_j^{\ 2}\right)^2 + \left(z_j - 1\right)^2$	-100	100	m = 30
$\mathbf{F_6(z) = Step}$	$F_6(z) = \sum_{j=1}^{m} \left(\left[z_j + 0.5\right]\right)^2$	-100	100	m = 30
$\mathbf{F_7(z) = Quartic}$	$F_7(z) = \sum_{j=1}^{m} j z_j^{\ 4} + \text{randm}\ [0,1]$	-100	100	m = 30
$\mathbf{F_8(z) = Schwefel}$	$F_8(z) = \sum_{j=1}^{m} - z_j \text{Sin}\left(\sqrt{\lvert z_j \rvert}\right)$	-100	100	m = 30
$\mathbf{F_9(z) = Rastrigin}$	$F_9(z) = \sum_{j=1}^{m} \left[z_j^{\ 2} - 10\text{Cos}\left(2\pi z_j\right) + 10\right]$	-100	100	m = 30
$\boldsymbol{F_{10}(z)} = \mathbf{Ackley}$	$F_{10}(z) = -20\exp\left(-0.2\left(\frac{1}{m}\sum_{j=1}^{m} z_j^{\ 2}\right)^{\wedge}0.5\right) - \exp\left(\frac{1}{m}\sum_{j=1}^{m} \text{Cos}\left(2\pi z_j\right)\right) + 20 + e$	-100	100	m = 30

Ten benchmark test functions' mean values have been generated by the algorithms. It is clear from the data in table 4.3 that the suggested algorithm performs better than the other methods under comparison. The primary objective of the benchmark test function is to evaluate the performance of the newly developed algorithm (DACO).

Table 4.3 Statistical analysis result of mean value of benchmark function

Algorithms	$F_1(z)$	$F_2(z)$	$F_3(z)$	$F_4(z)$	$F_5(z)$	$F_6(z)$	$F_7(z)$	$F_8(z)$	$F_9(z)$	$F_{10}(z)$
PSO	3.55	4.3E+01	3.15E+01	2.53E+03	8.254E+02	7.21	7.13E-02	-8.1E+02	3.15E+02	2.42E+01
DE	3.54E-03	7.57E-04	9.08E+02	2.32E+01	3.22E+02	6.13	1.54E-02	-5.27E+03	3.51E+01	2.77
ABC	2.21E-01	3.41E-01	7.65E+01	4.46E-02	3.32E+03	2.23E-02	5.12E-01	-6.71E+03	3.52E+02	2.56E-01
GWOCS	2.41E-08	2.21E-03	7.21E-11	3.45E-09	1.46E+02	3.32E-01	7.51E-03	-8.21E+02	5.20E-10	5.32E-22
ACO	2.63E-23	5.36E-38	6.16E-21	2.55E-07	1.36E+03	2.32E-02	2.32E-02	-0.87E+03	3.62E-13	4.23E-03
DACO	6.65E-56	1.71E-65	2.33E-93	6.64E-70	1.67	5.32E-05	4.32E-04	-2.36E+04	4.65E-32	5.37E-15

Based on the test results, it can be inferred that the suggested method outperforms the other algorithms in terms of mean values across ten benchmark test functions, convergence rate, robustness, precision, and overall performance.

4.7 Justification of benchmark function

The PEM fuel cell is a multimodality structure, it can be observed that its output is controlled by a variety of characteristics. Because parameters can be changed to achieve the desired result, three multimodality and seven unimodality benchmark functions is selected to test the randomized behaviours of the output and compare it with the benchmark function to determine its acceptability. Figure 4.4 to figure 4.13 showcase the comparison bar chart of DACO with other algorithms in each benchmark test function (F1 to F10) depicting the mean value The performance of the other algorithms such as PSO, DE, ABC, GWOCS, and ACO were compared with the proposed DACO algorithm (Yang et al., 2014, Fergany et al., 2018, Han et al., 2019).

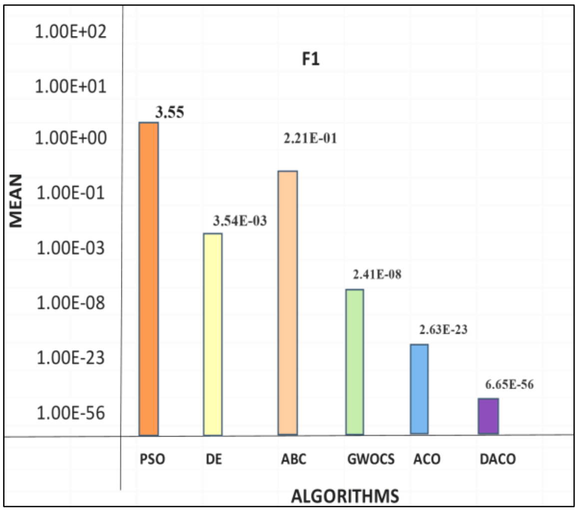

Figure 4.4 The benchmark function's mean is represented in a bar chart, F1

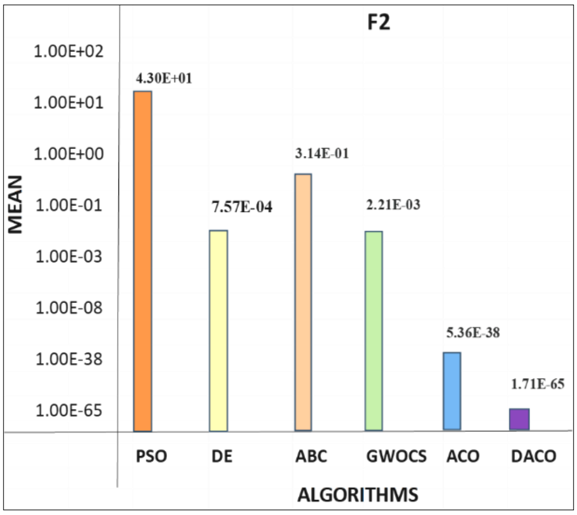

Figure 4.5 The benchmark function's mean is represented in a bar chart, F2

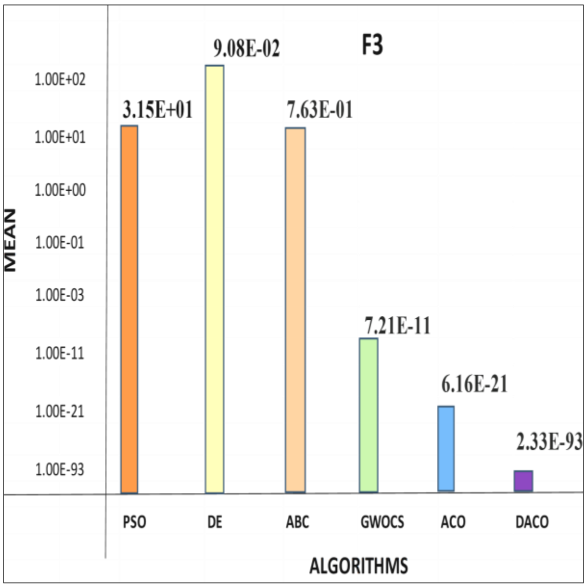

Figure 4.6 The benchmark function's mean is represented in a bar chart, F3

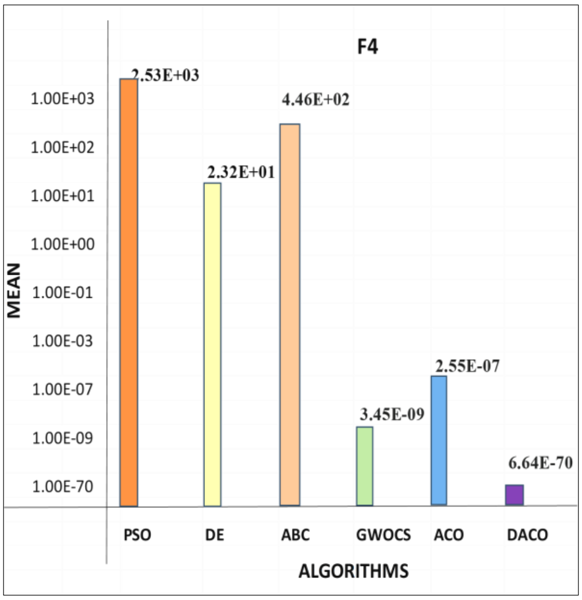

Figure 4.7 The benchmark function's mean is represented in a bar chart, F4

When the population size is very high, these functions are more effective for assessing the algorithm's scalability. To test the global minima that the DACO method achieves for the extremely large size population within acceptable bounds, the Schwefel, Rastrigin, and Ackley function has been selected.

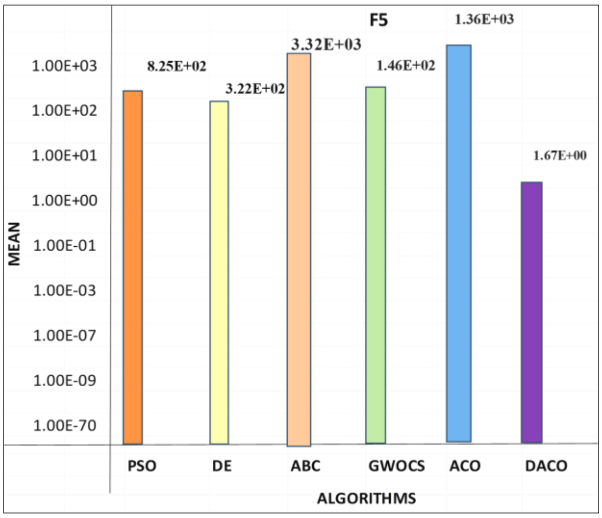

Figure 4.8 The benchmark function's mean is represented in a bar chart, F5

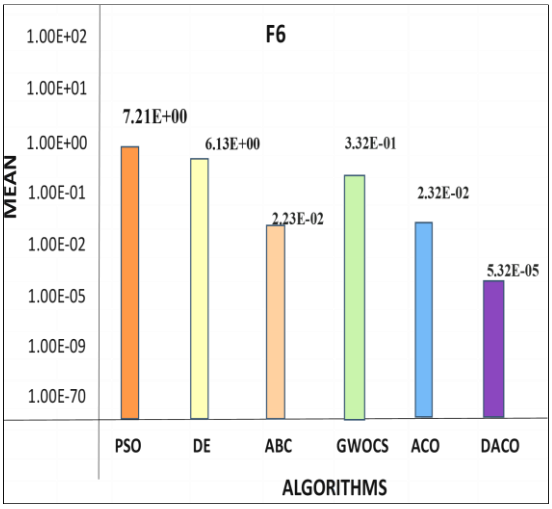

Figure 4.9 The benchmark function's mean is represented in a bar chart, F6

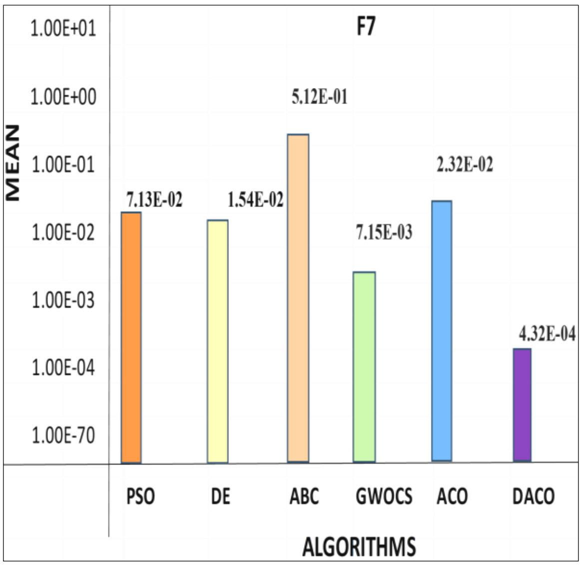

Figure 4.10 The benchmark function's mean is represented in a bar chart, F7

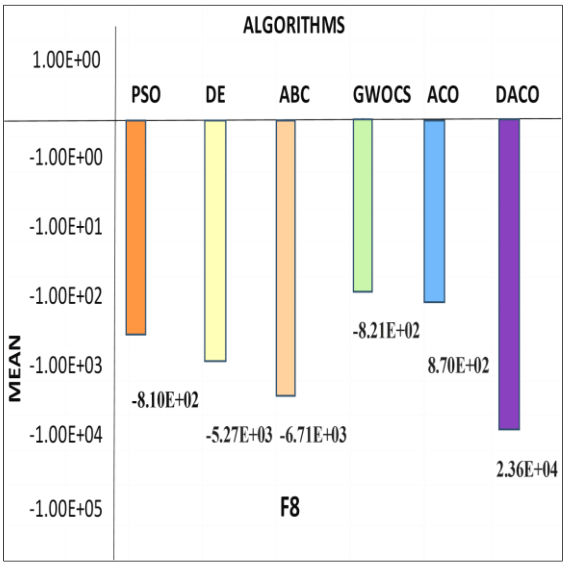

Figure 4.11 The benchmark function's mean is represented in a bar chart, F8

There is no linear relationship between the input and output variables in the PEM fuel cell equation. The adaptability of the function to ascertain the approximate path taken by the DACO has been tested using the Rosen-Brock benchmark function.

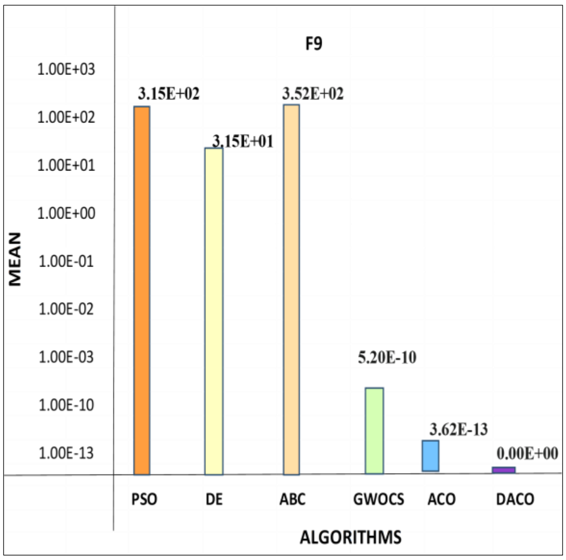

Figure 4.12 The benchmark function's mean is represented in a bar chart, F9

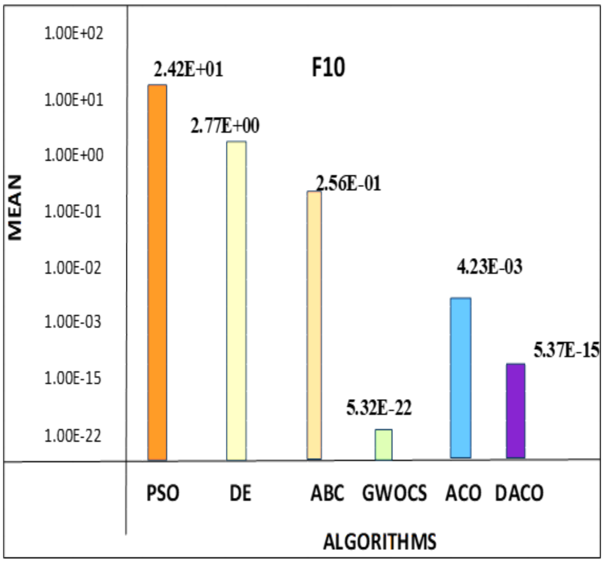

Figure 4.13 The benchmark function's mean is represented in a bar chart, F10

Additionally, Rosen-Brock guarantees that the function in question is simple in nature, with its minima situated within the valleys of the parabolic function. This guarantees the DACO algorithm's convergence throughout the nth iteration. For complex dynamic search strategies in nonlinear optimization issues, the Step, Sphere, and Quartic functions guarantee the potential optimization of the nonlinear search space that are countered during transition from i^{th} to j^{th} node.

4.8 PEMFC parameter extraction

The issues surrounding the extraction of model parameters for the Ballard Mark V PEMFC are the main emphasis of this section (Chen et al., 2019, Guarnieri et al., 2016).The goal in doing this is to better comprehend DACO's performance. Table 4.4 displays the PEMFC model's parameter search range. The relevant data sheet can be found here. A number of well-known meta-heuristic algorithms, such as PSO, DE, ABC, GWOCS, and ACO, is analyzed in order to assess DACO performance (Askarzadeh et al., 2013, Zhang et al., 2013). To provide a fair comparison between DACO and the other algorithms under consideration, a dimension of 30 iteration and a constant number of feature evaluations (between -100 and +100) are set. The codes were implemented in MATLAB r2022b, and each procedure was run 30 times independently.

Table 4.4 Parametric values of PEMFC

Parameters / Algorithm	a_0	a_1*10^-3^	a_2*10^-5^	a_3*10^-4^	R_{Cs} (Ω)* 10^-4^	b (V)	κ
PSO	−0.949	3.470	3.86	−0.948	1.049	0.0350	18.847
DE	−0.988	3.322	6.442	−0.9543	6.48	0.0261	15.769
ABC	−0.852	2.952	4.614	-0.9540	2.47	0.0299	14.273
GWOCS	−0.852	3.387	7.428	−0.9543	1.68	0.0240	14.044
ACO	−1.029	3.555	7.659	−0.9541	1.23	0.0368	13.460
DACO	−1.095	3.412	7.931	−0.954	0.8	0.0182	14.080

4.9 Statistics analysis

Calculated and measured voltage and absolute error of model Ballard Mark V PEMFC is represented in Table 4.5. According to the results in table 4.6, In terms of Sum Squared Error (SSE), it is clear that the DACO method outperforms the other algorithms. When compared to previous methods, the suggested DACO algorithm has demonstrated a much shorter computing time.

Table 4.5 Calculated and measured voltage and absolute error of model Ballard Mark V

Current measured (A)	Voltage measured (V)	Voltage calculated (V)	Absolute Voltage error (V)
2.3	0.91	0.906	0.004
8.7	0.88	0.874	0.006
14.1	0.84	0.836	0.004
18.7	0.81	0.812	0.002
25.3	0.78	0.775	0.005
30.2	0.76	0.767	0.007
36.3	0.73	0.731	0.001
42.3	0.71	0.721	0.011
47.5	0.68	0.678	0.002
53.6	0.65	0.653	0.003
58.9	0.61	0.605	0.005
63.7	0.59	0.580	0.010
68.7	0.55	0.547	0.003

Table 4.6 Statistics analysis of different algorithm

Algorithm	Sum Squared Error (SSE)	Computational Time (sec)
PSO	7.3E-03	5.26
DE	3.5E-03	3.70
ABC	3.8E-03	4.28
GWOCS	2.3E-04	3.25
ACO	2.5E-04	2.57
DACO	1.4E-05	3.09

4.10 Convergence analysis

The convergence curves of the PEMFC model are investigated, as displayed in figure 4.15, using a variety of optimization methods, such as PSO, DE, ABC, GWOCS, and ACO, in order to assess the efficacy of the DACO computation (Brest et al., 2006, Abdollahzadeh et al., 2014). Each of these algorithms was tested using the same number of fitness evaluations. The results are illustrated in figures 4.4 to 4.13. Convergence curves in figure 4.14 states that DACO exhibits a quicker rate of convergence than the other methods in comparison to others.

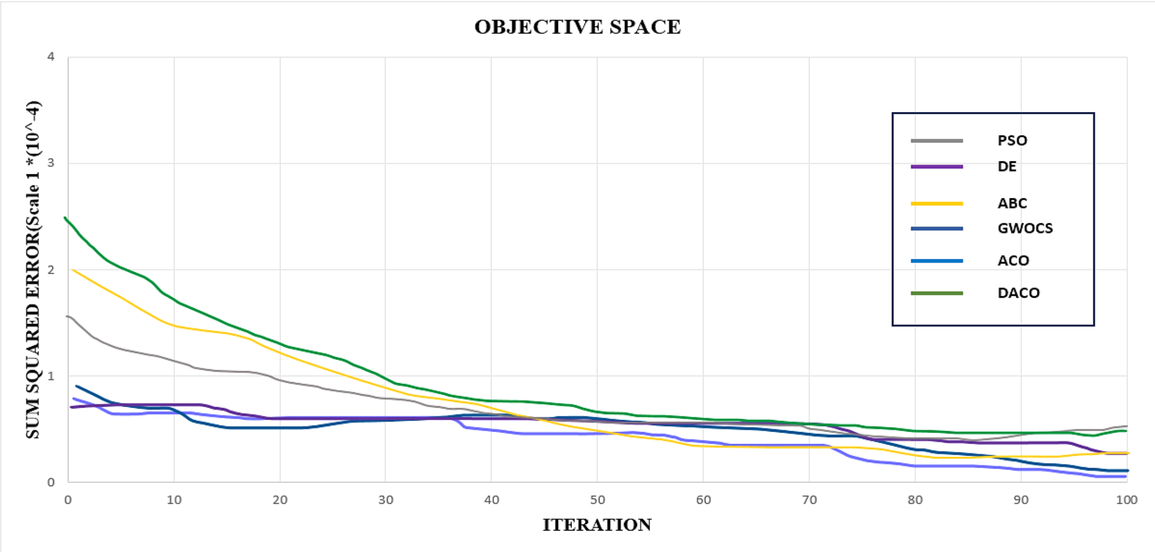

Figure 4.14 Convergence analysis of different algorithms

4.11 Summary on PEMFC optimization using DACO

In a PEMFC parameter extraction task, the paper contrasts six metaheuristic optimization algorithms: PSO, DE, ABC, GWOCS, ACO, and DACO. The performance and operation of the non-linear model in the governing equations are determined by seven elements. The SSE between the measured and predicted PEMFC voltage is used as the fitness function in this study, which focuses on novel Dynamic ACO from PSO, DE, ABC, GWOCS, and ACO. A 1000-Watt Ballard Mark V is used as a novel case study to determine the parameters of the

PEMFC model, and the results show excellent agreement between the estimated and observed values under various operating situations.

The investigation's findings indicate that, in terms of the best SSE in both case studies, DACO performs marginally better than PSO, DE, ABC, GWOCS, and ACO. However, with a 20% improvement in the lowest SSEs, the data unequivocally demonstrate that DACO outperforms alternative metaheuristic algorithms in these particular scenarios. To address global optimization and determine extract parameters from diverse PEMFC models with varying temperatures and partial pressures of hydrogen and oxygen, a new algorithm named DACO is being introduced (Shojayian et al., 2024, Jahromi et al., 2021).

Initially 10 test benchmark functions were used in this work to validate the suggested algorithm. Comparing DACO to other algorithms, the mean value it achieved in 10 benchmark functions shows that it is close to zero. The following are the conclusions drawn from the results:

• The statistical result, which demonstrates that DACO works better than the other algorithms taken into consideration, amply demonstrates its superiority.

• Using the proposed metaheuristic optimization techniques to develop a more thorough PEMFC model that can forecast output voltage in the event that input parameter changes; evaluating the performance of the novel optimization algorithm in the research's case study extracted as indicated in table 4.6.

This chapter has helped in eradicating the problem that was faced by Artificial Neural Networks, when the parameters were larger in numbers. The hidden layer prediction methods were not sufficient to handle all the controlling parameters as with increase in the parameter leads to the higher complexity where the hidden layer concept fails in estimating the parameter. The Dynamic Ant Colony Optimization has performed well in handling the larger number of the controlling parameters by method of explore, search and update. This type of algorithms doesn't follow the conventional methods of brute forcing. All the possible combination of controlling parameters which result in larger time complexity to generate effective output of the PEMFC cell. Here, in this chapter it has been observed that the proposed DACO algorithm has performed well. However, the number of parameters that have been considered as controlling parameters for PEMFC were not too large. The number of controlling parameters of fuel cell available are much larger in numbers. Their behaviour in optimization can vary depending on the methods of approaches. In the next chapter, the optimization of the controlling parameters will be explored in greater context with new meta-heuristic algorithm i.e, Wild Chimpanzee Hunting Optimization (WCHO) algorithm based on Particle Swarm Optimization algorithm.

CHAPTER 5

Optimization of PEMFC using Wild Chimpanzee Hunting Optimization algorithm

5.1 Introduction

Proton Exchange Membrane Fuel Cells (PEMFCs) are becoming widely recognized as a promising alternative to non-renewable energy sources due to their sustainability, reliability, lack of self-discharge, and pollution-free operation. As a result, these fuel cells are utilized in various applications. Accurate determination of PEMFC parameters is essential. The simulation, study, and design of highly efficient fuel cells rely heavily on precise estimation of their characteristics. The operation of a fuel cell involves a carefully controlled chemical process that converts chemical energy into electrical energy. A fuel cell comprises an electrolyte situated between the anode and cathode, which are the main components of the cell. Given the growing significance of (Smith et al., 2010) PEMFCs and their increasing use in industrial settings, it is crucial to develop and refine a more accurate model to understand the core mechanisms within the fuel cell and enhance its efficiency. As in previous chapter it was tried to achieve the best optimum result of Mean Square Error (MSE) using dynamic Ant Colony Optimization (Alaya et al., 2007) algorithm and further it was compared with several other metaheuristic algorithm like PSO, DE, GWOCS, ABC, ACO. There have been numerous attempts to create more accurate models for determining the roles of PEMFC. The study, simulation, and development of efficient and high-performing fuel cells highly depend on the modelling of PEMFCs attributes. Parameter estimation of PEMFCs, as illustrated in figure 3.3 of the previous chapter, presents an optimization challenge due to insufficient statistics in the model's datasheet. There are two approaches to address this problem: meta-heuristic algorithms and conventional methods. Traditional methods often fall short in precision due to the non-linear characteristics. On the other hand, meta-heuristic algorithms offer a random initial guess, guarantee convergence to a global optimal solution, and are capable of solving intricate problems.

In previous chapter it has been discussed how DACO (Ghosh et al., 2024) outperforms other all metaheuristic algorithm like DE, PSO, ABC, ACO, GWOCS. The iteration time as well as sum squared values obtained there is very much close to optimum in view of context. A novel optimization technique namely Wild Chimpanzee Hunting optimization is introduced in this chapter and tried to analyse the previous condition with this new optimization technique. Now it has been observed that if computational time is not so concerning then the results obtained for mean sum squared error is even less or closer to DACO, which gives some advantage in obtaining further more optimized results.

5.2 Problem optimization expression

Table 5.1 Lower and Upper bound range of PEMFC Parameters

Parameter	Parametric Range	
	Upper	**Lower**
a_0	-8.53*10^{-1}	-1.1996
a_1	500*10^{-5}	100*10^{-5}
a_2	9.8*10^{-5}	3.6*10^{-5}
a_3	-0.954*10^{-4}	-2.60*10^{-4}
R_{Cs} (Ω)	8*10^{-4}	1*10^{-4}
b (V)	0.5	0.0136
κ	24.00	10.00

The main optimization function is defined below which to minimize the sum squared error. Is given by following expression.

$$MIN(F = \sum_{i=1}^{N}(V_{\text{measured}} - V_{calculated})^2) \qquad [59]$$

Table 5.2 Lower and Upper bound range of PEMFC Parameters

Parameter	Parametric Range	
	Upper	Lower
a_0	$-8.53*10^{-1}$	-1.1996
a_1	$500*10^{-5}$	$100*10^{-5}$
a_2	$9.8*10^{-5}$	$3.6*10^{-5}$
a_3	$-0.954*10^{-4}$	$-2.60*10^{-4}$
R_{Cs} (Ω)	$8*10^{-4}$	$1*10^{-4}$
b (V)	0.5	0.0136
κ	24.00	10.00

Data Statement for the parameter estimation and inputs are mentioned in table 5.1. All the optimizing parameter along with their range have been mentioned in table 5.2.

Nomenclature

$(V_{FC})_O$	Fuel Cell Open voltage
V_{FC}	Actual Fuel Cell output voltage
R_{ohm}	Membrane Resistance
E_C	Open circuit voltage of single cell
R	Universal gas constant
F	Faraday constant
T_S	Stack temp.

Z No. of Electron Transferred

n_C No. of Cells

$$(V_{FC})_O = E_C + \frac{RT_S}{ZF} ln\left[\frac{P_{H_2}.\sqrt{(P_{O_2})}}{P_{H_2O}}\right] \quad [60]$$

$$V_{\text{stack}} = n_c((V_{FC})_O - (V_{loss}{}^{Act} + V_{loss}{}^{Ohm} + V_{loss}{}^{Conc})) \quad [61]$$

$$V_{loss}{}^{Act} = a_0 + T_S\left[a_1 + a_2\, ln(\,C_{O_2}) + a_3\, ln(\,I)\right] \quad [62]$$

$$V_{loss}{}^{Ohm} = IR_{ohm} \quad [63]$$

$$V_{\text{concentration}} = -b\, ln\left(I - \frac{\varphi}{\varphi_{\max}}\right) \quad [64]$$

The detailed description of above all expression has already been discussed in chapter 4. The other all mathematical expression regarding fuel cell are elaborated in previous chapter.

5.3 Wild Chimpanzee Hunting Optimization algorithm

The chimpanzees are very clever animals, it lived in groups. It usually feed on the fruits and wild roots, but sometimes the wild chimpanzees hunt other small monkeys. It has very sharp eyes that can catch any movements in the branches of the trees. The hunting behaviour of the monkeys plays a methodical procedure while hunting down their prey, based on the hunting behaviour of the wild chimpanzee, an optimization technique which forage the hunting behaviour of the wild chimpanzees, has been developed.

Let Xn= $\{X_1, X_2, X_3 \ldots\ldots X_n\}$ be the population of the wild chimpanzees.

During hunting the troop of the chimpanzees has to chase their prey very fast, that jumps from one branch to another as shown in figure 5.1. During chasing the chimpanzees usually follow the movement caused by the prey or the other member of the troop.

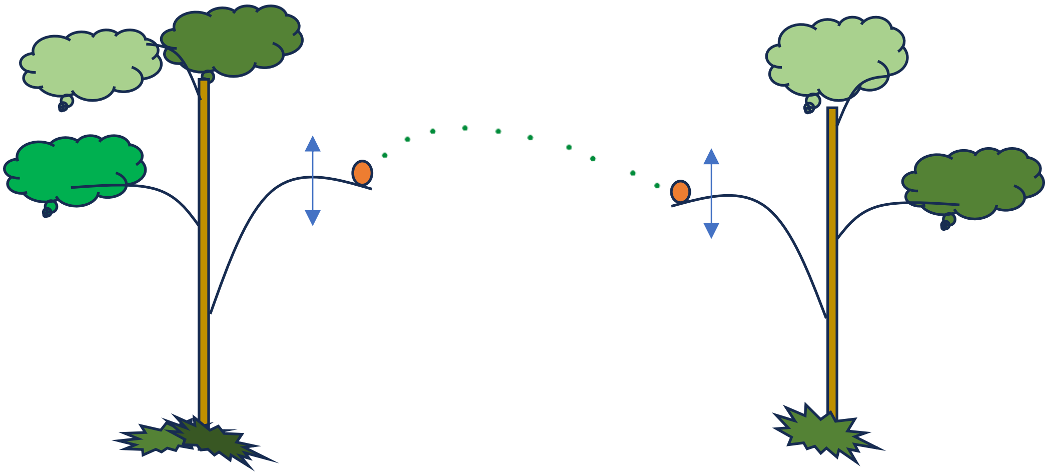

Figure 5.1 Position transition from one branch to another

Thus, the swing caused by the chimpanzee by jumping to any branch can be expressed as

$$T_{ij}^{X} = 2\pi\sqrt{\frac{m}{k_{ij}}} \qquad \begin{cases} m\ is\ the\ mass\ of\ the\ prey\ /\ predator \\ k\ is\ the\ force\ per\ unit\ displacement \end{cases} \qquad [65]$$

T^X is the oscillation produced by the prey during moving from i^th^ branch to j^th^ branch. The oscillation produce in the branch is directly proportionate to the root over of mass of the prey or the predator and inversely to applied force per unit displacement. Turbulence caused by mass of prey is crucial for the study of next move of chimpanzee which is graphically shown in figure 5.2.

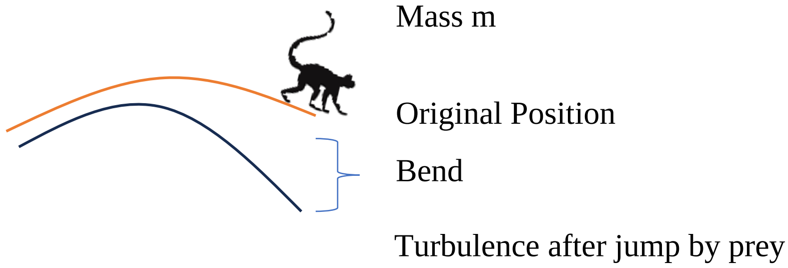

Figure 5.2 Turbulence caused by mass of prey

Thus, the chimpanzees will choose the branch which will have higher oscillation as compared to the other branches which can be expressed as

Probability of choosing branch $T_{ij}^{X} = \dfrac{2\pi\sqrt{\frac{m}{k_{ij}}}}{\sum_{l=0}^{n} h \in all\ path\ 2\pi\sqrt{\frac{m}{k_{ih}}}} * \alpha$ [66]

where $\alpha = \begin{cases} 0\ when\ wind\ is\ blowing \\ 1\ when\ wind\ is\ not\ blowing \end{cases}$

The existence of the wind energy is more important in tracing the path followed by the prey. Here when wind is blowing, there is turbulence in all the branches of the trees, which make it more difficulty for the chimpanzees to distinguish which movement was caused by the prey or the wind. This result in the choosing wrong path in choosing the trees where the prey has jumped to escape from being hunt. Here α is a random value that is used to depict the behaviour of the wind. When the value of the α is “0” the system probability turns out to be zero. Thus, invalidating the selected paths as there may be many more branches with some oscillation when wind is blowing.

5.3.1 Distance calculation between two jumps points

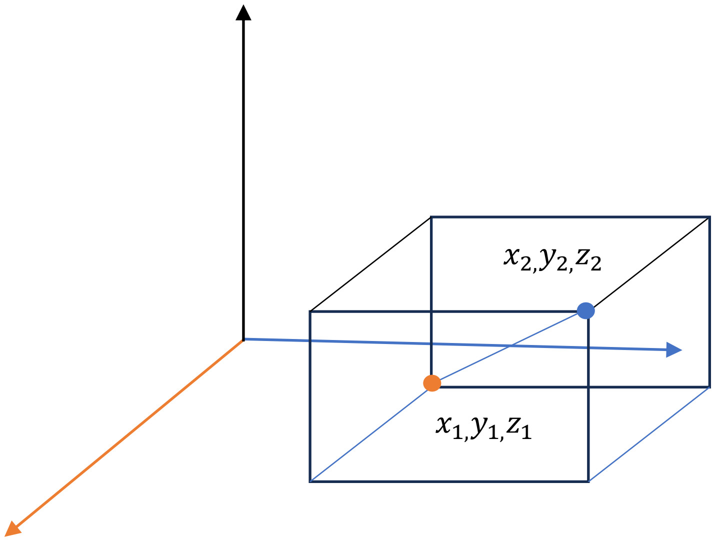

Figure 5.3 Locus of point in 3D space

During the hunting of the prey by the Chimpanzee the prey usually jumps from one branch of the tree to another branch. Here the initial jump coordinate can be assumed to $x_{1,}y_{1,}z_1$ and the branch where it lands can be assumed to $x_{2,}y_{2,}z_{2.}$ The figure 5.3 represent here represent the distance between the two consecutive jumps in the free 3d space can be calculated as follows

$$d = \sqrt{(x2 - x1)^2 + (y2 - y1)^2 + (z2 - z1)^2} \begin{cases} x_{1,}y_{1,}z_1 \; \textit{are the position at branch u} \\ x_{2,}y_{2,}z_2 \; \textit{are the position at branch v} \end{cases} \quad [67]$$

Here d can be used to find the distance between the jumps from one branch to another.

Accordingly best or optimal path can be selected by the formula

$$d_{ij} = \frac{d_{ij}}{\sum_{l=0}^{n} d_{hj}} \quad \left\langle \text{where h is all path traversed by the chimpanzees} \right\rangle \quad [68]$$

5.3.2 Path update phenomenon in WCHO algorithm

The path updating mechanism of the WCHO algorithm is derived from the PSO (Eberhart et al., 1995) algorithm where the individual best score is tallied from the group best score, if the best score of individuals is greater than the best score of the group is updated with that best score. Figure 5.4 represented below shows the chasing approach in WCHO.

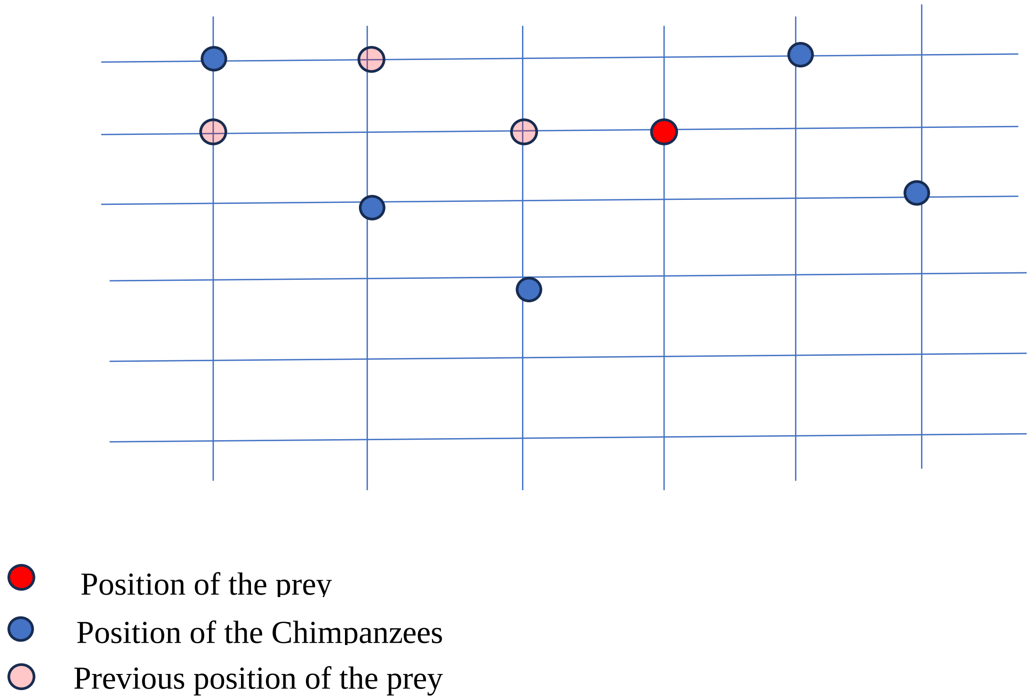

Figure 5.4 Chasing approach in WCHO

$$T_{ij}^{X+1} \leftarrow \left(\frac{}{2\pi\sqrt{\frac{m}{k_{ij}}}}\right) best - \left(\frac{}{2\pi\sqrt{\frac{m}{k_{ij}}}}\right) current + \left(\frac{}{d_{ij}}\right) best - \left(\frac{}{d_{ij}}\right) current + d_{uv} \qquad [69]$$

Where d_{uv} is the initial start position.

$d_{uv} = \{ \; Random_{ij}$ value generated for initializing the start position.

Here, if the position of the current chaser chimpanzee is closer than the group best position then the value of the group best is updated with that of the current chaser chimpanzee.

5.3.3 Flow chart WCHO algorithm

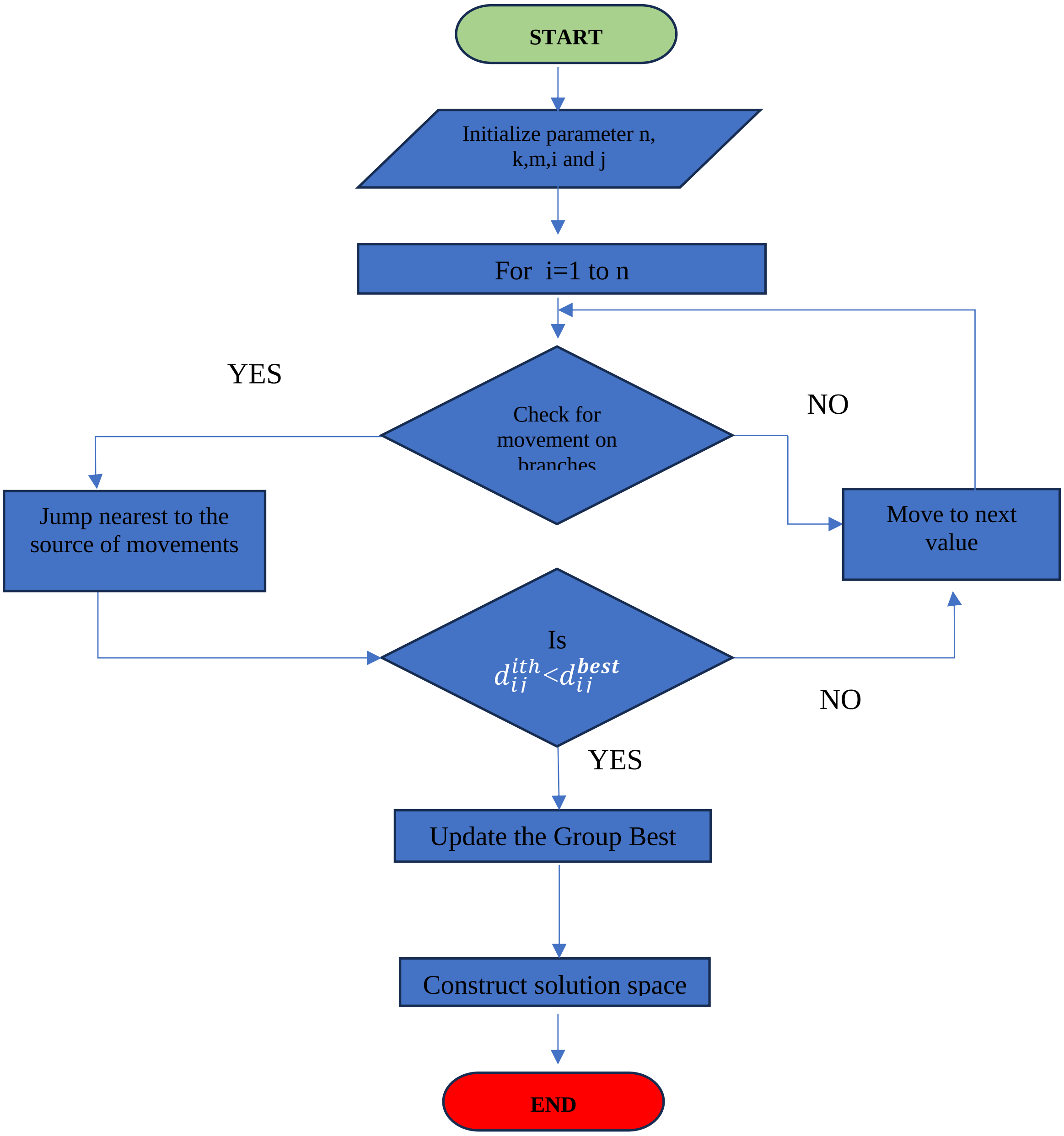

Figure 5.5 Flow chart of Wild Chimpanzee Hunting

The flow chart of WCHO gives a detailed route path of proposed study of algorithm which is chronologically shown in figure 5.5.

5.4 Problem formulation and experimental results

Optimization algorithms are instrumental in discovering the most optimal solution to estimate the parameter of PEMFC. In this research article, a Wild Chimpanzee Hunting Optimization is introduced for the precise and accurate parameter estimation in PEMFC (Smith et at., 2010, Askarzadeh et al., 2010). Utilizing optimization algorithms, predictions are made for the output voltage based on different current density inputs. Furthermore, the evaluation measure used to compare the anticipated output voltage produced from optimization algorithms with the experimental values of the output voltage is the sum of square error (SSE) (Tummala et al., 2024, Kennedy et al., 1995). Experimental results are obtained here by testing the algorithm using ten benchmark function, which are shown in table 5.3, here it can be seen that the iteration of each function is ranged from -100 to 100 with a dimension of 30. The equation no 70 represents the objective function as:

Table 5.3 Test benchmark functions used in proposed algorithm

Function Name	Function	Min	Max	Dimension
$F_1(z)$ = Sphere	$F_1(z) = \sum_{j=1}^{m} z_j{}^2$	-100	100	m = 30
$F_2(z)$ = Schwefel 2.22	$F_2(z) = \sum_{j=1}^{m} \lvert z_j \rvert + \prod_{j=1}^{m} \lvert z_j \rvert$	-100	100	m = 30
$F_3(z)$ = Styblinski – Tang function	$F_3(z) = \dfrac{\sum_{i=1} z_i^4 - 16z_i^2 + 5z_i}{2}$	-100	100	m = 30
F_4 = Rosen-brock	$F_4(z) = \sum_{j=1}^{m} 100\left(z_j + 1 - z_j{}^2\right)^2 + \left(z_j - 1\right)^2$	-100	100	m = 30
$F_5(z)$ = Step	$F_5(z) = \sum_{j=1}^{m} \left(\left[z_j + 0.5\right]\right)^2$	-100	100	m = 30
$F_6(z)$ = Shekel function	$F_6(z) = \sum_{j=1}^{m} 100\left(z_j + 1 - z_j{}^2\right)^2 + \left(z_j - 1\right)^2$	-100	100	m=30
$F_7(z)$ = Three Hump Camel function	$F_7(z_i, z_j) = 2z_i{}^2 - 1.05z_i{}^4 + \frac{z_i{}^6}{6} + z_i z_j + z_j^2$	-100	100	m=30
$F_8(z)$ = Easom function	$F_8(z_i, z_j) = -\cos(z_i)\cos(z_j)\exp\left(-((z_i - \pi)^2 + (z_j - \pi)^2\right)$	-100	100	m=30
$F_9(z)$ = Easom function	$F_9(z_i, z_j) = 0.26\left(z_i^2 + z_j^2\right) - 0.48z_i z_j$	-100	100	m=30
$F_{10}(z)$ =Bukin function N.6	$F_{10}(z_i, z_j) = 100\sqrt{\lvert z_j - 0.01z_i^2 \rvert} + 0.01\lvert z_i + 10 \rvert$	-100	100	m=30

$$MIN(F = \sum_{i=1}^{N}(V_{\text{measured}} - V_{calculated})^2) \quad [70]$$

5.4.1 Test using benchmark function

The mean of different benchmark function is represented by bar chart which will be observe later in this section. Function F1 through F7 are unimodal, whereas function F8 through F10 are multimodal. As in case of previous comparison which is discussed earlier in chapter 4, here also Wild Chimpanzee Hunting optimization is compared with other metaheuristic algorithm, and some of concluding remarks has been drawn which will be discussed later in this chapter Several meta-heuristics algorithms, such as PSO, ACO, ABC, GWOCS, and DACO are compared with the WCHO performance. Function F1 represent the mean of benchmark function showing nearly close results of WCHO with DACO.

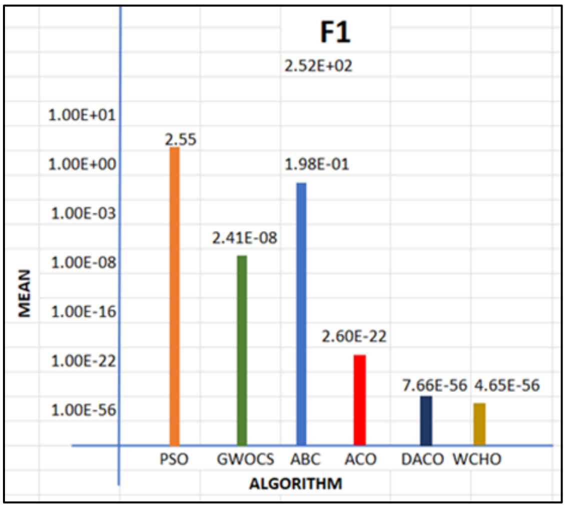

Figure 5.6 Bar chart representation of mean of benchmark function F1

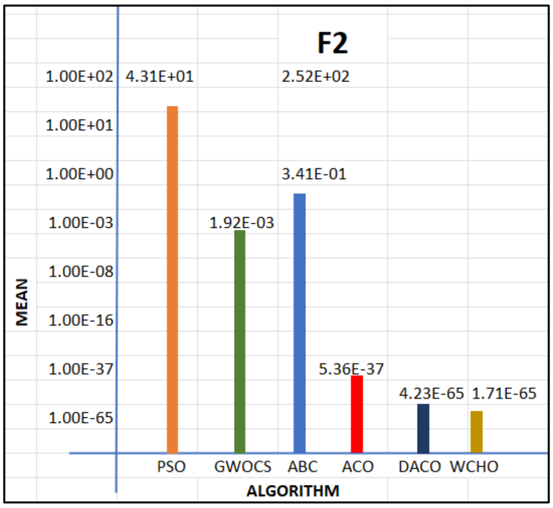

Figure 5.7 Bar chart representation of mean of benchmark function F2

The results of mean obtained from different benchmark function F1 to F10 are shown from Figure 5.6 to Figure. 5.15 gives the details comparison of WCHO with other all metaheuristic algorithms. Every curve gives consistent results as compared to Dynamic Ant Colony optimization.

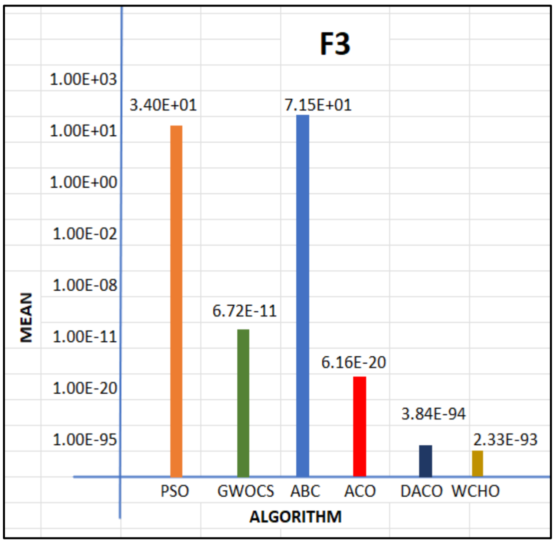

Figure 5.8 Bar chart representation of mean of benchmark function F3

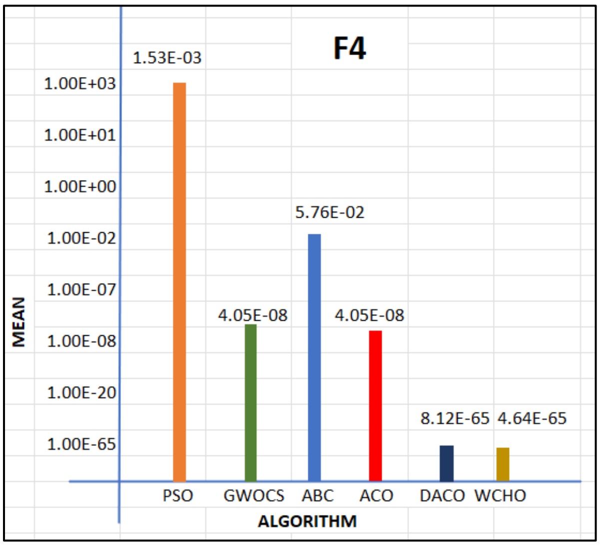

Figure 5.9 Bar chart representation of mean of benchmark function F4

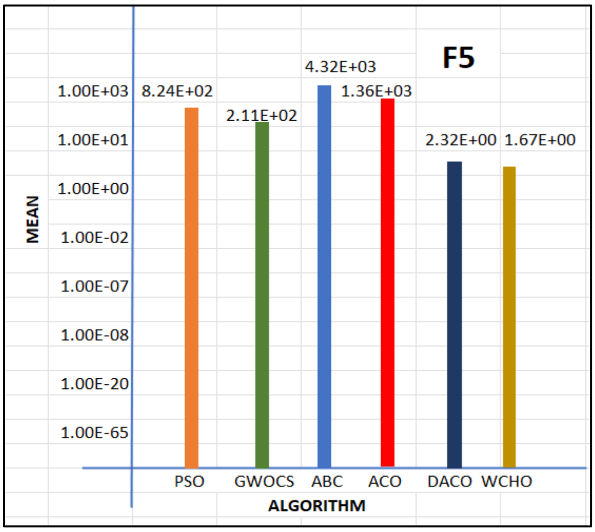

Figure 5.10 Bar chart representation of mean of benchmark function F5

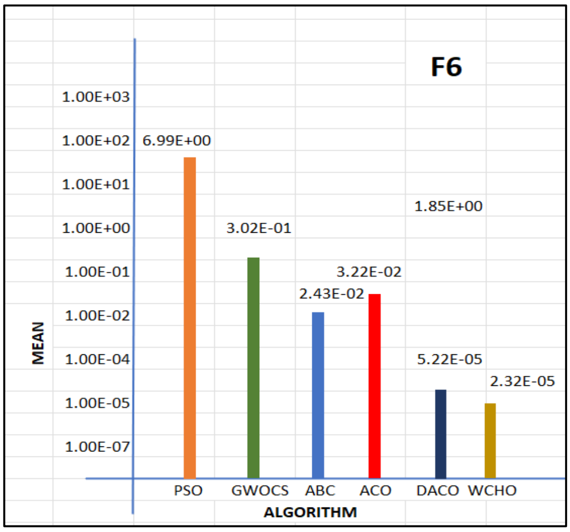

Figure 5.11 Bar chart representation of mean of benchmark function F6

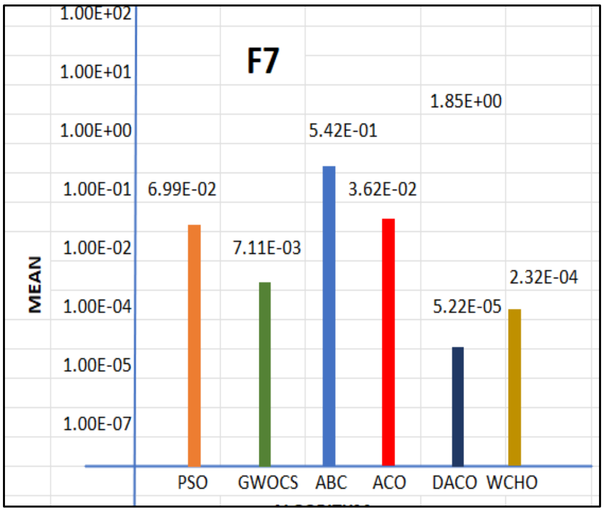

Figure 5.12 Bar chart representation of mean of benchmark function F7

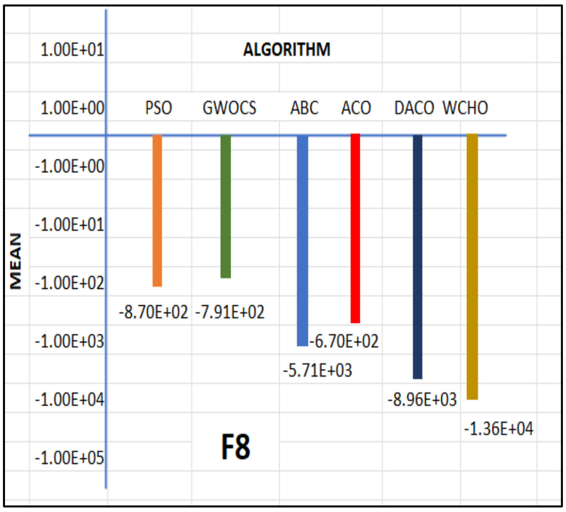

Figure 5.13 Bar chart representation of mean of benchmark function F8

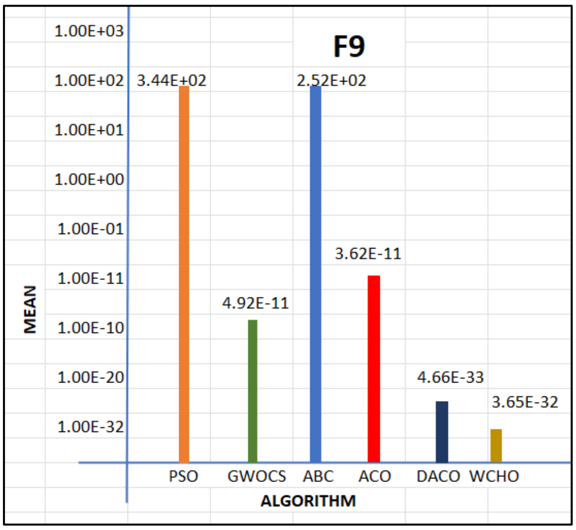

Figure 5.14 Bar chart representation of mean of benchmark function F9

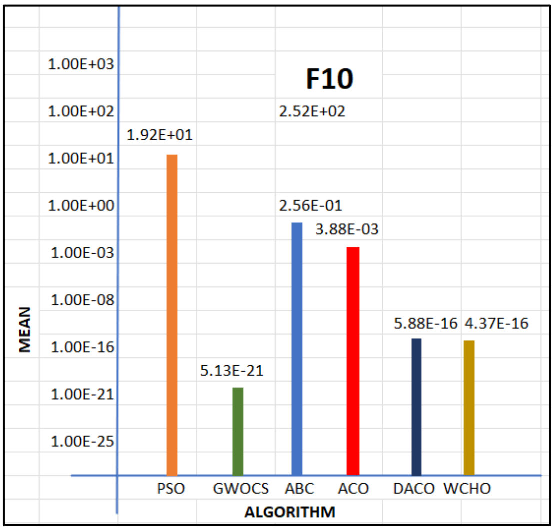

Figure 5.15 Bar chart representation of mean of benchmark function F10

5.4.2 Justification of benchmark function

Given that the PEM fuel cell is a multimodality system, it can be observed that its output is controlled by n number of parameters. As parameters can be altered to attain the desired result, three multimodality and seven unimodality benchmark functions were obtained to test the randomised behaviour of the output and compare it with the benchmark function to determine its acceptability. When the population size is very large, these functions are more effective at assessing the algorithm's scalability. To test the global minima that the WCHO algorithm achieves for the very large size population within acceptable bounds, the Schwefel, Styblinski-Tang function has been selected. There is no linear relationship between the input and output variables in the PEM fuel cell equation.

Table 5.4 Statistical analysis result of mean value of benchmark function

Algorithm	$\mathbf{F_1(z)}$	$\mathbf{F_2(z)}$	$\mathbf{F_3(z)}$	$\mathbf{F_4(z)}$	$\mathbf{F_5(z)}$	$\mathbf{F_6(z)}$	$\mathbf{F_7(z)}$	$\mathbf{F_8(z)}$	$\mathbf{F_9(z)}$	$\mathbf{F_{10}(z)}$
PSO	**2.55**	**4.31E+01**	**3.40E+01**	**1.53E+03**	**8.24E+02**	**6.99**	**6.99E-02**	**-8.7E+02**	**3.44E+02**	**1.92E+01**
ABC	**1.98E-01**	**3.41E-01**	**7.15E+01**	**5.76E-02**	**4.32E+03**	**2.43E-02**	**5.42E-01**	**-5.71E+03**	**2.52E+02**	**2.56E-01**
GWOCS	**2.41E-08**	**1.921E-03**	**6.721E-11**	**4.05E-08**	**2.11E+02**	**3.02E-01**	**7.11E-03**	**-7.91E+02**	**4.92E-10**	**5.3E-21**
ACO	**2.6E-22**	**5.36E-37**	**6.16E-20**	**2.57E-07**	**1.36E+03**	**3.32E-02**	**3.62E-02**	**-0.67E+03**	**3.62E-11**	**3.88E-03**
DACO	**7.66E-56**	**4.23E-65**	**3.84E-94**	**8.12E-65**	**2.32**	**5.22E-05**	**5.22E-05**	**-8.96E+3**	**4.66E-33**	**5.88E-16**
WCHO	**4.65E-56**	**1.71E-65**	**2.33E-93**	**4.64E-65**	**1.67**	**2.32E-05**	**2.32E-04**	**-1.36E+04**	**3.65E-32**	**4.37E-16**

Additionally, the PEM fuel cell functions do not exhibit a linear relationship between their input and output variables. The Rosen-brock function ensures that the given function is simplistic, with its minima located between the valleys of the parabolic function. This feature guarantees the convergence behaviour of the WCHO algorithm over multiple iterations.

The Step, Sphere, and Quartic functions are used to optimize the nonlinear search space, addressing dynamic search strategy challenges encountered during the transition between nodes. Statistical analysis result of mean value of benchmark function from F1 to F10 is represented in table 5.4.

5.5 Result and Discussion

The result obtained in this section is depends on statistical analysis of PEMFC parameter extraction and convergence analysis. Both of these analyses are discussed in subsequent sections.

5.5.1 PEMFC parameter extraction and statistical analysis

The extraction of parameter is important objective as these parametric values will be provide required values of overall efficiency of PEMFC. The parameters and their corresponding Sum Squared Error (SSE) values for the PEMFC model are determined under standard temperature conditions (STC) and are displayed in table 5.5 for the Ballard Mark V PEMFC. The results in table 5.5 clearly demonstrate that the DACO and WCHO algorithm outperforms other algorithms regarding SSE.

Table 5.5 Parametric values of PEMFC

Parameters / Algorithm	a_0	a_1 *10^{-3}	a_2 *10^{-5}	a_3 *10^{-4}	R_{Cs} (Ω)* 10^{-4}	b (V)	κ
PSO	−0.949	3.470	3.86	−0.948	1.049	0.0350	18.847
DACO	−1.095	3.412	7.931	−0.954	0.8	0.0182	14.080
ABC	−0.852	2.952	4.614	-0.9540	2.47	0.0299	14.273
GWOCS	−0.852	3.387	7.428	−0.9543	1.68	0.0240	14.044
ACO	−1.029	3.555	7.659	−0.9541	1.23	0.0368	13.460
WCHO	-1.102	3.458	8.12	-1.01	0.76	0.0210	14.620

Additionally, the proposed DACO algorithm significantly reduces computational time compared to the other algorithms. The SSE values and Computational Time of PEMFC are tabulated in table 5.6.

Table 5.6 Statistics analysis of different algorithm

Algorithm	Sum Squared Error (SSE)	Computational Time (sec)
PSO	7.3E-03	5.26
ABC	3.8E-03	4.28
GWOCS	2.3E-04	3.25
ACO	2.5E-04	2.57
DACO	1.4E-05	2.97
WCHO	1.22E-05	3.81

5.5.2 Convergence analysis

In the comprehensive analysis presented in the previous chapter, it was noted that by assessing the efficiency of the DACO calculation, the convergence curves of the PEMFC model, obtained through different optimization algorithms, were evaluated. These algorithms were tested using the same number of fitness evaluations. In this chapter WCHO is also analysed along with DACO and other all algorithm, the curve as shown in figure 5.16 shows that the result of curve obtained from WCHO is very much closer to that of DACO.

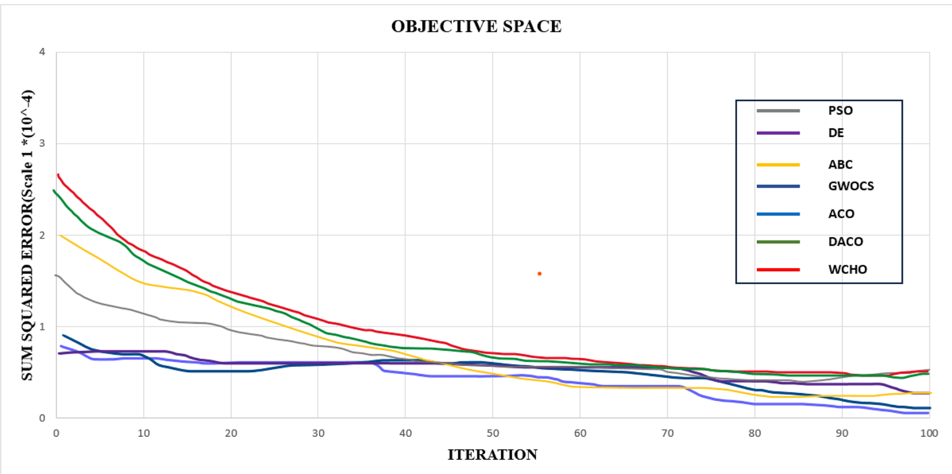

Figure 5.16 Convergence curve of all algorithm

5.6 Limitation of the WCHO algorithm

The WCHO Algorithm has its own limitation. The WCHO algorithm will not be able to trace the prey monkeys, where there are no turbulences in the branches of the trees. The situation can be expressed as follows:

If there is two or more equal best individual value which are greater than group average value then there is a problem of selecting which path to be followed.

5.7 Summary on PEMFC optimization using WCHO algorithm

The study examines six metaheuristic optimization algorithms, namely PSO, ABC, GWOCS, ACO, DACO, and WCHO, in the context of PEMFC parameter extraction. The non-linear model is characterized by seven factors that influence its performance and operation within the governing equations. The research focuses on comparing the new WCHO optimization technique with DACO, PSO, DE, ABC, GWOCS, and ACO, utilizing the Sum Squared Error (SSE) between measured and predicted PEMFC voltage as the fitness function. The parameters for the PEMFC model are identified for a new case study involving a 1000-Watt Ballard Mark V, showing excellent agreement between calculated and measured values under various operating conditions.

The findings indicate that WCHO slightly outperforms PSO, DACO, ABC, GWOCS, and ACO regarding the best SSE in both case studies. However, DACO demonstrates a shorter computation time compared to other algorithms. Overall, the results reveal that WCHO significantly surpasses other metaheuristic algorithms in specific cases, achieving a 20% improvement in the lowest SSEs. The study introduces a new algorithm, DACO, to tackle global optimization and extract parameters from various PEMFC models under different temperatures and partial pressures of hydrogen and oxygen.

Here are the outlined findings based on the obtained results:

• The statistical finding, which shows that WCHO and DACO both outperforms the other algorithms considered, is a clear indication of its superiority.

• the SSE values are more justifying in case of WCHO as compared to DACO and other all algorithm.

• If iteration timing is given priority, then DACO is better metaheuristic algorithm.

As the computational time is much less in DACO than WCHO and SSE is considerably better in DACO. So DACO has been used to optimized the parameters of PID and FOPID controller in next chapter.

CHAPTER 6

Optimization of PID Controller using Dynamic Ant Colony algorithm in a DC/DC converter for performance enhancement of PEMFCs

Optimization of PID parameters using the Dynamic Ant Colony Algorithm in a DC/DC Converter for Performance Enhancement of PEMFCs in *Springer Nature*, Edited Vol. (*2025*) (Accepted). ISBN:978-981-96-3840-6

6.1 Introduction

Fuel cells transform fuel's chemical energy into electrical energy, resulting in high efficiency, lesser emission of petrol, and flexible modular architecture. Proton-exchange membrane fuel cells, or PEMFCs, are concise in design, light in weight with desirable output power density at low temperatures. Among their many applications are mobile vehicles, emergency backup power sources and compact power supply. Challenges like inadequate efficiency, uncontrolled voltage, and excessive fuel consumption make them unusable in most situations. So models of conventional PID, Dynamic Ant Colony Optimization-based PID, Dynamic Ant Colony Optimization-based Fractional Order PID, Particle Sum Optimization-based PID, Particle Sum Optimization-based FOPID, BEE Colony-based PID, and BEE-Colony-based FOPID controllers were developed and compared using Simulink in order to enhance PEMFC performance. In this work, PEMFC performance has been analysed using rates of different methodology (Jemeı et al., 2003, Saengrung et al., 2007).

PEMFCs are feedback control systems used in industrial and technical applications. Traditionally, Proportional-integral (PI) or proportional-integral-derivative (PI) controllers are considered to optimize parameters in PEMFCs. These controllers minimize the discrepancy comparing the actual system response with the specified setpoint by utilizing derivative (D), integral (I), and proportional (P) components. Parameter optimization is required for the system design using conventional integer-order PID. Other strategies, such as heuristic approach and artificial intelligence techniques, were employed in addition to the Ziegler-Nichols method. However, as a result of the variables' nonlinear dynamics, these approaches are not useful for conducting fractional operations optimally. For this reason, researchers frequently choose fractional-order controllers because of their accuracy, adaptability, and flexibility in producing precise results (Liu et al., 2017, Singh et al., 2023).

Heuristic optimization methods like ant colony, particle swarm, and artificial bee colony are utilized in PID and FOPID controller-based PEMFC studies. Although the optimal solution may not always be guaranteed by these intuitive approaches, they have improved PEMFCs that use the parameters of PID controllers, which are established by these techniques. The Artificial Bee Colony's theoretical analysis is taken into consideration in this work, along with its difficulty, convergence time uncertainty, and variations in probability distribution. The development of the Dynamic Ant Colony Optimization (DACO) algorithm results from modifying the Ant Colony Optimisation (ACO) approach to take parameter changes into consideration. The PSO and DACO optimisation approach is the recommended option in this study because it is more straightforward, efficient, and readily effective (Routh et al., 2023, Routh et al., 2024). A Schematic diagram of PEMFC system in shown in figure 6.1.

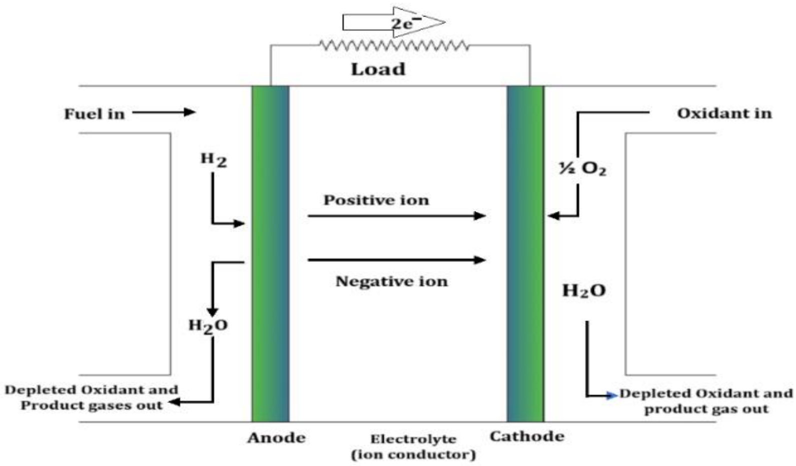

Figure 6.1 Schematic diagram of PEMFC system

The article addresses the use of different controllers to improve PEMFC performance, by considering the variables like the value of the fitness function, settling time (T_S), and the percentage of maximum overshoot (M_P%). These controllers include conventional PID, PSO-based PID, PSO-based FOPID, Artificial Bee Colony-based PID (ABC-PID), ABC-FOPID, Dynamic Ant Colony-based PID, and DACO-based FOPID (Routh et al., 2024).

The rest portion of this paper is organized accordingly: The newly proposed model is described in later part together with the PID-controlled DC/DC converter, PEM fuel cell, FOPID, PSO, PSO-FOPID, ABC and ABC-FOPID, DACO and DACO-FOPID fitness functions, including ITAE, ISTE, and IAE. The results acquired through IAE, ITAE, and ISTE are stipulated in Section 6.3. The last Section 6.4 provides the final conclusions (Ghosh et al., 2019).

6.1.1 Problem formulation and methods

This PEM fuel cell is observed here with a traditional PID-controlled DC/DC converter as the techniques employed in this investigation. To further optimize the PID controller parameters, the Artificial Bee Colony Optimization (ABC), Dynamic Ant Colony Optimization (DACO), PSO-based FOPID, ABC-based FOPID, and DACO-based FOPID techniques were put into practice. This section also includes a full description of the model used in this study, including its specifics. Moreover, simulation performed with the MATLAB/SIMULINK programmed was used to assess the overall system performance. The Matlab Simscape module was used to create the model (Ghosh et al., 2024, Kumar et al., 2022).

6.1.2 PEM fuel cell application in DC/DC converter

The PEM fuel cell's components and structure provide the highest energy density. It makes use of hydrogen and oxygen as input parameters that have been catalyzed into electrons and protons as shown in figure 6.1. A number of variables, including reactant partial pressure, membrane humidity, cell temperature, and current density, might affect the non-linear nature of the anode reaction (Pahnehkolaei et al., 2022). Precise modelling and management of temperature can enhance efficiency and minimize the risk of being damaged. In fuel cells, there are three losses involved. These three types of losses include concentration, ohmic, and activation. A number of optimization strategies have been applied to reduce the losses. Here, we've suggested a DC-DC converter control method for PEM fuel cells to maximize fuel cell performance (Zhuang et al., 1993).

$$Anode \rightarrow 2H_2 \rightarrow 4H^+ + \{4e^-\} \quad [71]$$

The cathode interaction between oxygen and hydrogen ions produces water as a by-product. The fuel cell discharges moisture. At the cathode, the reduction reaction is:

$$Cathode \rightarrow O_2 + \{4e^-\} + \{4H^+\} \rightarrow 2H_2O \quad [72]$$

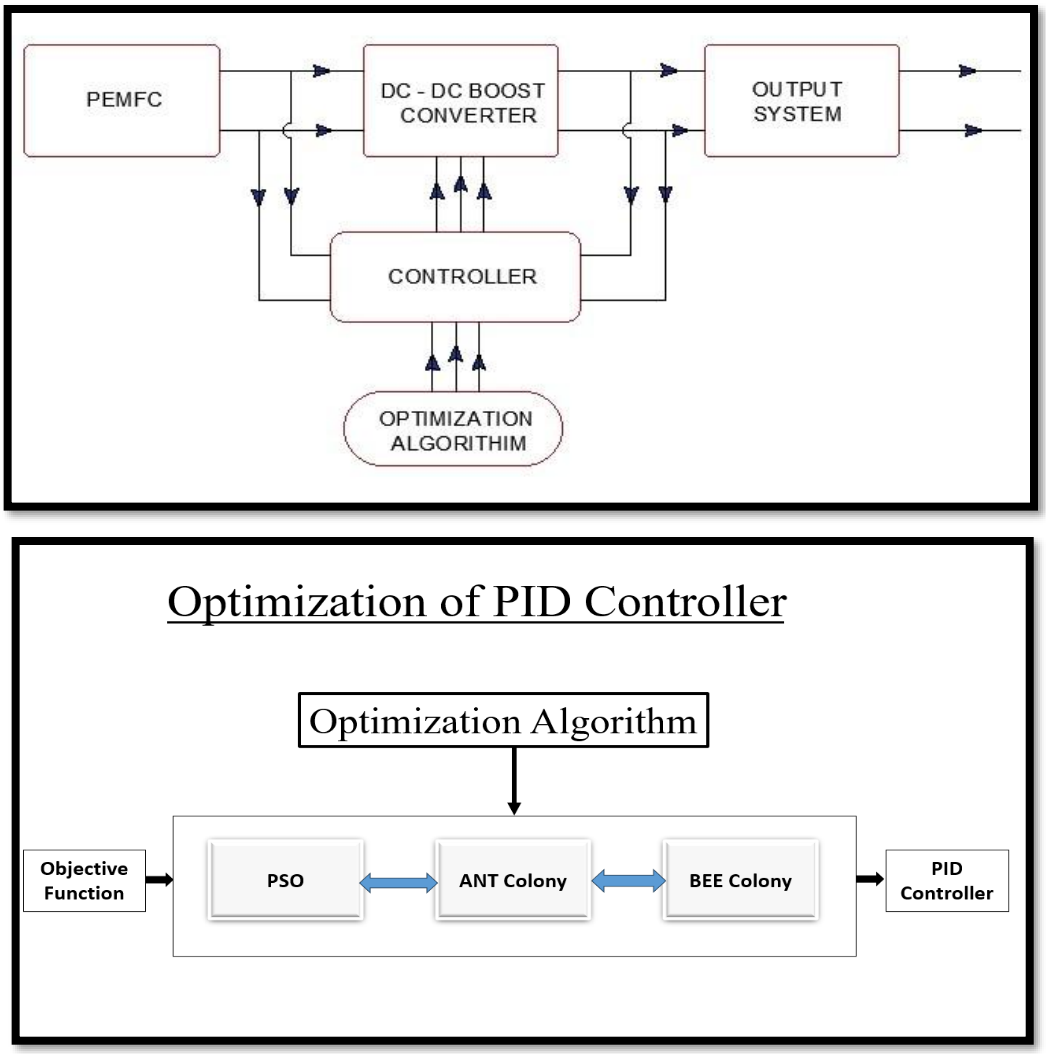

Figure 6.2 Block diagram representation of controller parameters' optimization technique

DC/DC Converter Application in PEM Fuel Cell

Figure 6.2 demonstrates the operation of closed loop continuous conduction mode DC/DC boost converter. The boost converter's key benefits are its increased efficiency and decreased component count. It also reduces the dimensions and expenses of energy storage elements by converting unregulated voltage into appropriate regulated voltage by altering the duty cycle at high switching frequencies. For a given switching frequency, it is crucial to choose such elements with boost inductive and capacitive value in order to minimize ripple generation. A small inductance permits the coil current to increase to greater levels prior to the switch shutting off, whereas high inductance marginally alters the startup time (Guldemir et al., 2011). This figure 6.3 shows the analogous circuit of the dc/dc boost converter at switch on and off times. The voltage drops across the inductor during the converter's on and off time is depicted in equations (85) under steady state conditions.

$$i_l(t) = \frac{1}{l} v_{\text{in}}\, t + i_l(0) \quad 0 \leq t \geq dT \tag{73}$$

$$i_l(t) = \frac{1}{l}(v_{\text{in}} - v_o)(t - dT) + i_l dT \quad dT \leq t \geq T \tag{74}$$

$$\frac{v_o}{v_{\text{in}}} = \frac{T_s}{t_{off}} = \frac{1}{1-D} \qquad v_{\text{in}} i_{\text{in}} = v_o i_o \tag{75}$$

$$\frac{v_o}{v_{in}} = \frac{1}{(1-D) + \frac{r_{fc}}{(1-D) r_l}} \; \frac{i_o}{i_{\text{in}}} = 1 - D \tag{76}$$

$$\text{Voltage Ripple} = \frac{dT_s}{rc} \tag{77}$$

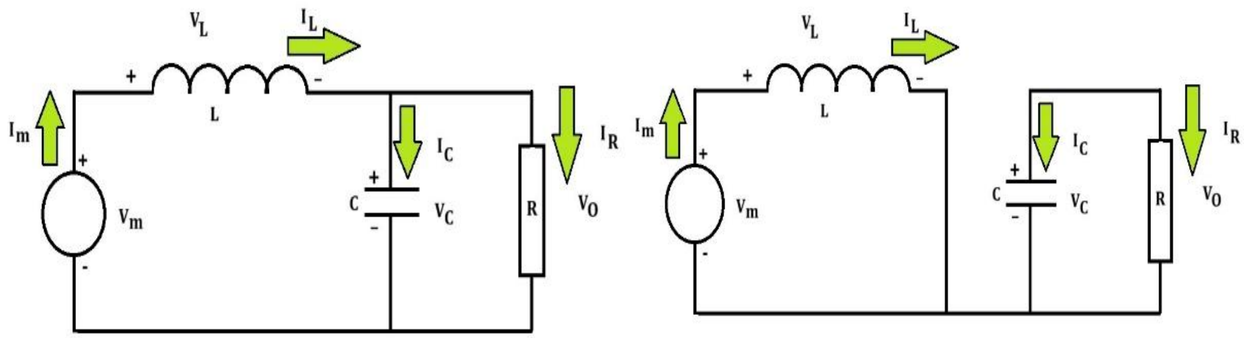

Figure 6.3 Circuit diagram representation DC-DC boost converter

Using the formulas from equation (85) to equation (89), the voltage ripple, the rated voltage, current ripple, and switching frequency of the converter may be used to calculate the size of the reactive elements of the boost converter.

6.1.3 The conventional PID controller in DC/DC converter

Stable electricity sources are essential for the industrial sector in the current environment. Because of its excellent efficiency, dynamic reactivity, and smooth speed control, DC-DC converters are the preferred option. These converters manage the output voltage by varying the input pulse's duty ratio and operating the converter switch off and on once every cycle. Output value consistency is crucial, thus PID control strategies are frequently chosen. Research has concentrated on modifying controller coefficients and stability in order to optimize PID controller performance. The Ǻström-Häggland approach, advanced Ziegler-Nichols method, Cohen-Coon rules, and Ziegler-Nichols are the most fundamental methods that have been documented in the literature. At the PEMFC's output in this investigation, a PID-controlled DC to DC converter was used (Dini et al., 2023). A generalized diagram is represented in figure 6.4 in section 6.2.

6.1.4 Fractional Order PID controller in DC/DC converter

The proposed FOPID controller integrates with various algorithms to provide accurate parameters for PEMFC, pointing the dynamic and non-linear model of PEMFC. This approach eliminates the drawbacks of large time delay and imperceptive response, ensuring system optimization and robustness.

$$V_{fc}(t) = K_p e(t) + K_i M^{-\lambda} e(t) + K_d M^{\mu} e(t) \tag{78}$$

Where, the operator M represent the calculus operator.

After Laplace Transformation the output of fuel cell will be

$$C(s) = K_P + K_I S^{-\lambda} K_D S^{\mu} \ , \in \lambda > 0 \ , \ \mu < 2 \tag{79}$$

6.1.5 Particle Swarm Optimization (PSO)-Based FOPID Controller

Particle swarm optimization (PSO) is a population-based stochastic optimization technique inspired by social behaviours such as bird flocking. Each particle in the swarm represents a potential resolution in the search objective. Particles adjust their positions based on their own experience (local best) and the collective experience of the swarm (global best). Velocity and position updates are governed by inertia, cognitive, and social components. PSO is efficient for continuous optimization problems but can struggle with high-dimensional or multimodal landscapes. Fine-tuning parameters like inertia weight and acceleration coefficients is crucial for balancing exploration and exploitation. The characteristics related to PSO include Particle Number (Swarm Size), Inertia Weight (w), Cognitive and Social characteristics (c1 and c2), and Maximum Velocity (V_{max}).

6.1.6 Artificial Bee Colony optimization (ABC)-based FOPID controller

A swarm intelligence programme called Artificial Bee Colony (ABC) was developed with inspiration from honey bee foraging behaviour. It uses three different kinds of bees: scout bees, employed bees, and observer bees. Using available food sources (solutions), employed bees search the area and report what they find to other bees. Onlooker bees select food sources based on their quality, determined by fitness function values. Scout bees are responsible for discovering new food sources by abandoning poor-performing ones after a certain number of unsuccessful iterations. ABC is effective for optimization tasks but may require careful parameter tuning, such as the number of employed bees and the limit for scout bee abandonments, to balance exploration and exploitation efficiently.

The i^{th} solution in the swarm is represented as $X_i = \{x_{i,1};x_{i,2};...;x_{i,D}\}$, where D is the dimension size. Each employed bee X_i produces a fresh potential solution Vi close to its current location in the manner described below.

$$v_{i,j} = x_{i,j} + \phi_{i,j} \cdot (x_{i,j} - x_{k,j}) \qquad [80]$$

X_k is a candidate solution which was randomly selected (i=k), Random dimension index j selected from the set $\{1,2,...,D\}$, and $\phi_{i,j}$ is a random number within $[-1,1]$. Greedy selection is used for generating candidate solution V_i. Update Xi with Vi if V_i 's fitness value is higher than that of its parent Xi; if not, leave Xi unchanged. Waggle dances are used by employed bees to alert other bees about their food sources once they have finished their hunt. An observer bee selects a food source based on a likelihood associated with its nectar content after assessing the nectar data collected from every working bee. This spinning wheel selection technique, which is really a probabilistic choice, is explained as follows.

$$p_i = \frac{\mathrm{fit}_i}{\sum_{j=1}^{\mathrm{SN}} \mathrm{fit}_j} \quad [81]$$

6.1.7 Dynamic Ant Colony optimization (DACO)-based FOPID controller

The idea of collective intelligence is illustrated by how well ants locate the optimal routes for getting food is the basis for the "ant colony" algorithm. The order fulfilment sequence is represented as an individual ant building its own route for every algorithm iteration. Each ant has to navigate the graph in order to come up with a solution. When selecting the next node, the ant will take into account the node's degree, which is supplied by δ(v). The greater the node's degree, the less probable it is that the ant will select that path. The ant will migrate from node i to node j at each step. With each iteration, the ant will thus produce the best solution possible, avoiding a node with a greater degree. For ant K, P^k_{ij} is the moving probability from state i to state j based on four values: the trail level function τ_{ij} move, as described by some heuristic indicating the prior desirability of that move δ_{ij}, the attractiveness function η_{ij} of the move, and the food probability of existence ∋ indicating how skilled it has been to make that specific move in the past. Using past data, the trail level is a way to assess if a change is acceptable.

$$P_{ij}^{k} = \frac{(\tau_{ij})^{\alpha} * (\eta_{ij})^{\beta} * \ni * (\delta_{\ ij})}{\sum_{k=0}^{m} h \in allowedj(\tau_{ih})^{\alpha} * (\eta_{ih})^{\beta} * \ni * (\delta_{\ ih})} \quad [82]$$

Where, m= maximum no. of unique path and τij signifies the quantity of pheromone deposited for travelling from node i to node j, 0 ≤ α is a parameter used to regulate the influence of the (τij) , (ηij) desirability of the state traversing ij and β ≥ 1 is a parameter used to regulate the influence of ηij. τij and ηij is used here as the trail level and the attractiveness of for the other possible state traversing (Özmen et al., 2020, Skinderowicz et al., 2022).

6.2 Model development

Application of PID Controller on Fuel Cell

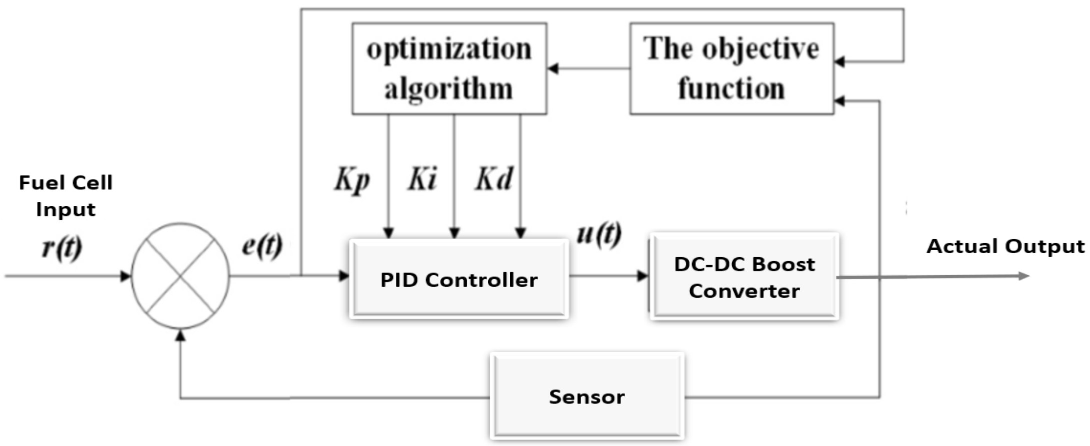

Figure 6.4 Generalized block diagram of PID controller and DC-DC boost converter is represented here with the optimization strategy

The procedure stages depicted in figure 6.4 are updated for every fitness function, including IAE, ITAE, and ISTE, in order to arrive at the ideal values. To increase the output performance of the PEMFC, the control of the DC/DC converter was done in this article using PID controllers, PSO-based PID controllers, PSO-based FOPID controllers, ABC-based PID controllers, ABC-based FOPID controllers, DACO-based PID controller, and DACO-based FOPID controller and MATLAB-Simulink model of PEMFC with DC-DC converter is shown in figure 6.5.

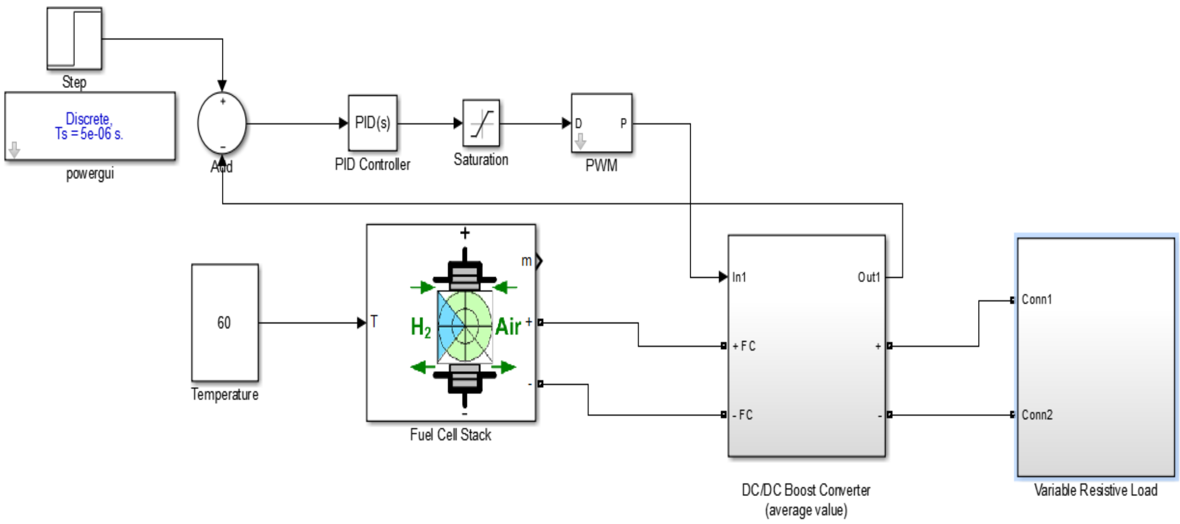

Figure 6.5 MATLAB-Simulink model of PEMFC with DC-DC converter

The DC voltage measured at PEMFC's output was sent into the DC/DC converter's input. The image illustrates how two different controller types—PID and $PI^{\lambda}D^{\mu}$—are used for a DC/DC converter, and how the optimization is done for their parameters by using PSO, ABC and DACO techniques. Figure 6.6 shows the V/I characteristic and parameter values of the PEMFC model which are utilized in this investigation.

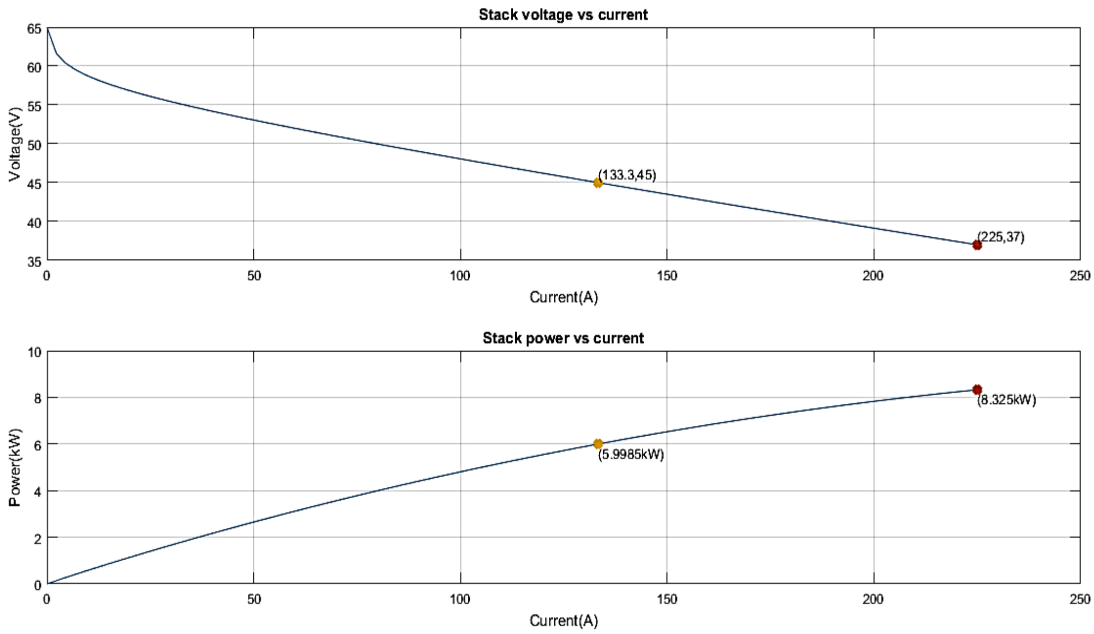

Figure 6.6 Stack voltage vs stack current and stack power vs stack current plot

6.2.1 Description of fitness function (IAE, ITAE, ISTE)

The fitness/objective functions selected for optimizing technique were the integral of square time error (ISTE), integral of absolute error (IAE), and integral of time absolute error (ITAE). The best values were found by reducing these errors associated with their route deviation (Fathy et al., 2021). The objective functions' theoretical expressions are provided below:

Integral of square time error $ISTE = \int_0^\infty t^2 \, e^2(t)dt$

Integral of absolute error $IAE = \int_0^\infty \|e(\,t)\|dt$

Integral of time multiplied absolute error $ITAE = \int_0^\infty t \, \|e(t)\|dt$

6.3 Result and discussion

In this research work, the optimized control strategy of a DC/DC boost converter have been studied with help of conventional PID, PSO-PID, PSO-FOPID, ABC-PID, ABC-FOPID, DACO-PID and DACO-FOPID controllers for improving the performance of PEMFC. The below mentioned section present here shows the outcome results of the applications.

6.3.1 Fitness Function IAE

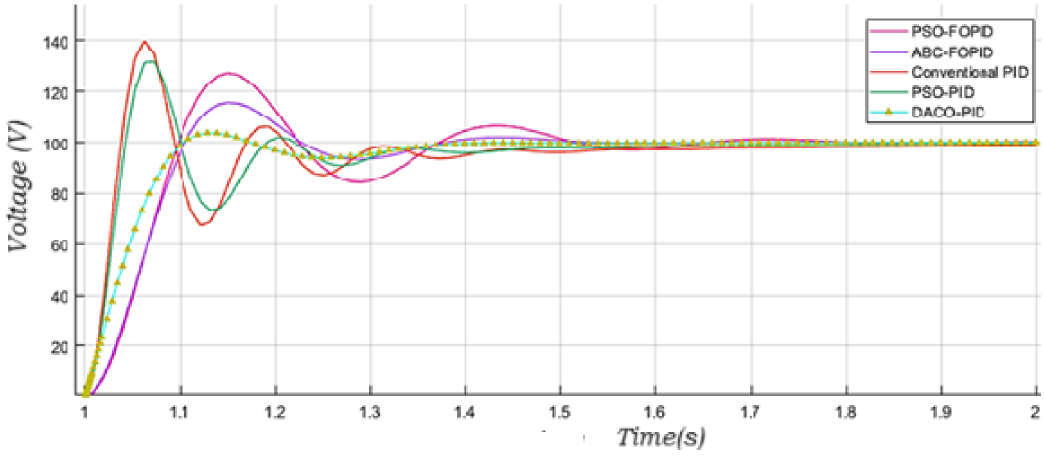

Figure 6.7 Controller response with the fitness function of IAE

The findings obtained in the IAE using the procedure described in figure 6.7. In this figure, the PSO-PID and PSO-FOPID applications were analysed using 10, 20, 30, 50 and 100 particles with 100 numbers iterations.

The lowest fitness function particles were identified. The PSO-FOPID study provided the lowest fitness function value with 100 particles, whereas the PSO-PID study produced the lowest value with 50 particles. The best results from PSO-PID and PSO-FOPID were then compared to results from other methods, including Conventional PID, ABC-PID, ABC-FOPID, DACO-PID, and DACO-FOPID. Controllers' performance was determined using fitness function value (Abdollahzadeh et al., 2021). The determined optimal parameters are also listed, as shown in table 6.1 & table 6.2.

Table 6.1 Controller parameters value with fitness function IAE

Methods	K_P	K_I	K_D	λ	μ
Conventional PID	0.1	0.2	3.2	------	------
PSO-PID	0.42	1.2	4.8	------	------
PSO-FOPID	0.36	1.04	3.2	0.13	0.08
ABC-PID	0.60	0.82	2.8	------	------
ABC-FOPID	0.55	0.78	3.2	0.08	0.10
DACO-PID	0.7	1.3	3.1	------	------
DACO-FOPID	0.73	1.46	4.1	0.12	0.15

Table 6.2 Comparison of the results with IAE

Methods	Fitness	M_P%	T_S
Conventional PID	------	168	750
PSO-PID	68.5	58	180
PSO-FOPID	23.30	52	190
ABC-PID	56.45	58	192
ABC-FOPID	29.32	60	185
DACO-PID	69	60	192
DACO-FOPID	27.23	53	182

6.3.2 Fitness Function ITAE

The study used in figure 6.8 methods and tested PSO-PID, PSO-FOPID applications. The PSO-FOPID study produced the lowest physical activity value for fitness-functioning particles, while the DACO-FOPID study produced the lowest for 100 particles (Shojayian et al., 2024).

The best results for both PSO-FOPID and DACO-FOPID were obtained. The parameters values are presented in table 6.3 and table 6.4 in the above section 6.3.1.

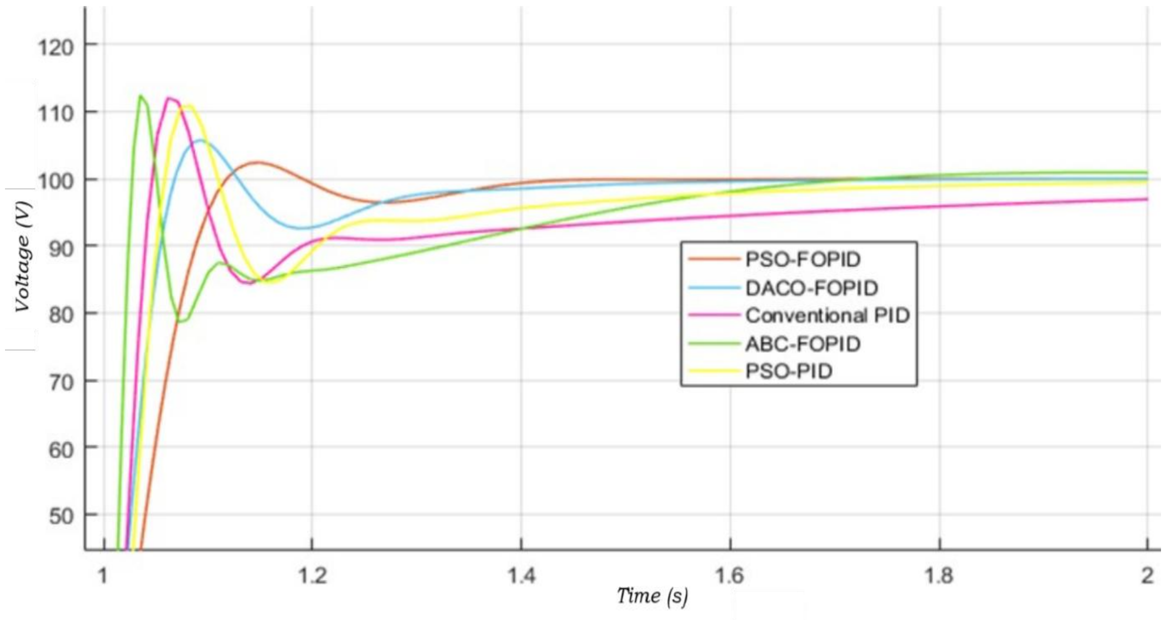

Figure 6.8: Controller response with the fitness function of ITAE

Table 6.3 Controller parameters value with fitness function ITAE

Methods	K_P	K_I	K_D	λ	µ
Conventional PID	0.14	0.6	2.1	-------	--------
PSO-PID	0.22	2.2	2.6	-------	-------
PSO-FOPID	0.32	1.84	1.8	0.28	0.04
ABC-PID	0.56	1.68	2.6	-------	-------
ABC-FOPID	0.51	1.38	2.8	0.48	0.08
DACO-PID	0.60	1.70	4.2	-------	-------
DACO-FOPID	0.64	1.26	3.6	0.42	0.13

Table 6.4 Comparison of the results with ITAE

Methods	Fitness Function ITAE	M_P%	T_S
Conventional PID	-----	188	680
PSO-PID	78.5	72	240
PSO-FOPID	33.20	66	220
ABC-PID	46.25	80	294
ABC-FOPID	30.56	75	268
DACO-PID	72.5	62	235
DACO-FOPID	76.23	60	230

6.3.3 Fitness Function ISTE

This is the last fitness function ISTE displayed in figure 6.9 which was obtained during the optimization of PEMFC with DC-DC boost converter.

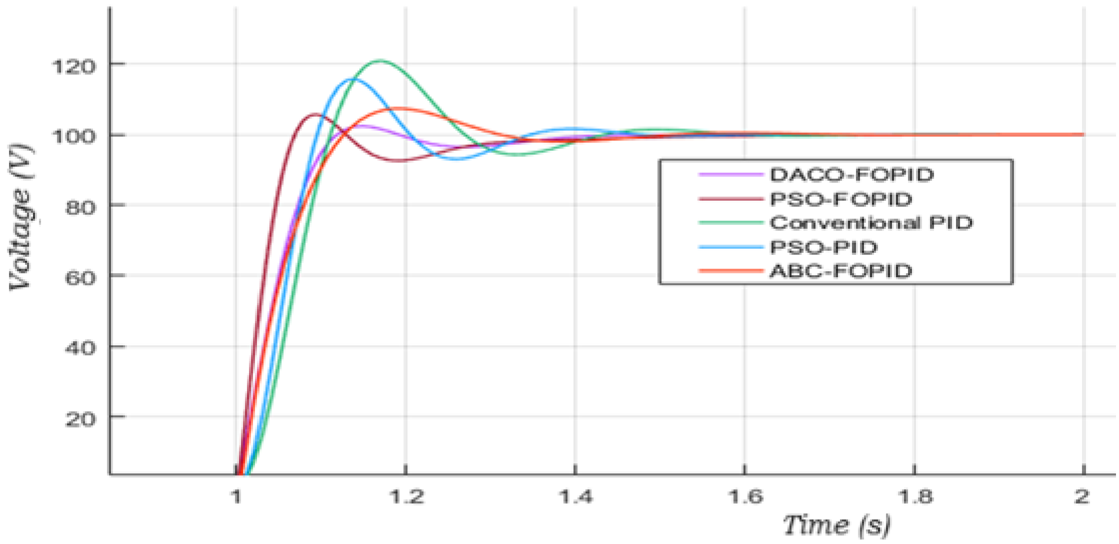

Figure 6.9 Controller response with the fitness function of ISTE

The ISTE fitness function was utilized for determining the optimum parameter values for controllers. The proposed methods outperformed the conventional PID method when considering MP% and T_S values. The PSO-FOPID & DACO-FOPID shows the best results, with M_P% = 59 & 54 respectively. Table 6.5 and table 6.6 represents the ISTE control parameters value.

Table 6.5 Controller parameters value with fitness function ISTE

Methods	K_P	K_I	K_D	λ	μ
Conventional PID	0.11	1.5	1.39	------	------
PSO-PID	0.06	2.1	1.76	------	------
PSO-FOPID	0.12	1.34	2.20	0.32	0.23
ABC-PID	0.26	1.26	1.45	------	------
ABC-FOPID	0.31	2.04	2.32	0.53	0.18
DACO-PID	0.20	2.4	3.04	------	------
DACO-FOPID	0.24	2.14	2.38	0.50	0.20

Table 6.6 Comparison of the results with ISTE

Methods	Fitness Function ISTE	M_P%	T_S
Conventional PID	------	178	570
PSO-PID	54.5	62	232
PSO-FOPID	26.50	59	215
ABC-PID	36.32	64	272
ABC-FOPID	38.70	58	256
DACO-PID	48.46	57	224
DACO-FOPID	44.52	54	218

6.4 Summary on PEMFC optimization using DACO algorithm in DC/DC converter

This article covers how the DC/DC converter used in PEMFC is controlled using a variety of controllers, including conventional PID, PSO-PID, PSO-FOPID, ABC-PID, ABC-FOPID, DACO-PID, and DACO-FOPID. Utilizing fitness functions like IAE, ISTE, and ITAE, the effectiveness of the suggested techniques was assessed as represented in figure 6.7, figure 6.8 and figure 6.9.

Fitness function value, maximum overshoot percentage (M_P%), and settling time (T_S) are considered as performance indicator of PEMFC (Yakut et al., 2024). The study consists of two stages, with the first stage involving the application of the proposed methods, identifying the optimum parameters using fitness function method. Using time settling (T_S) and maximum overshoot (M_P%) percent, the optimal approach was identified in the second step. The best performance was shown by the fitness functions derived from IAE and ISTE. According to the study's findings, the suggested strategies perform better than the traditional PID technique and use less power when a system first boots up. The approaches that are recommended in literature, namely PSO, ABC, DACO, and FOPID, also perform well in optimization research (Routh et al., 2022). The simulation results show that the PEMFC model with conventional PID and FOPID controllers, where controller parameters are tuned using PSO, ABC, and DACO, has acceptable control performance (Routh et al., 2024). Future research should focus on developing and applying these methodologies to various systems. As per the result obtained PSO-based-FOPID and DACO-based-FOPID controller shows superior performance among others (Ghosh et al., 2024).

CHAPTER 7

Conclusion

Conclusion

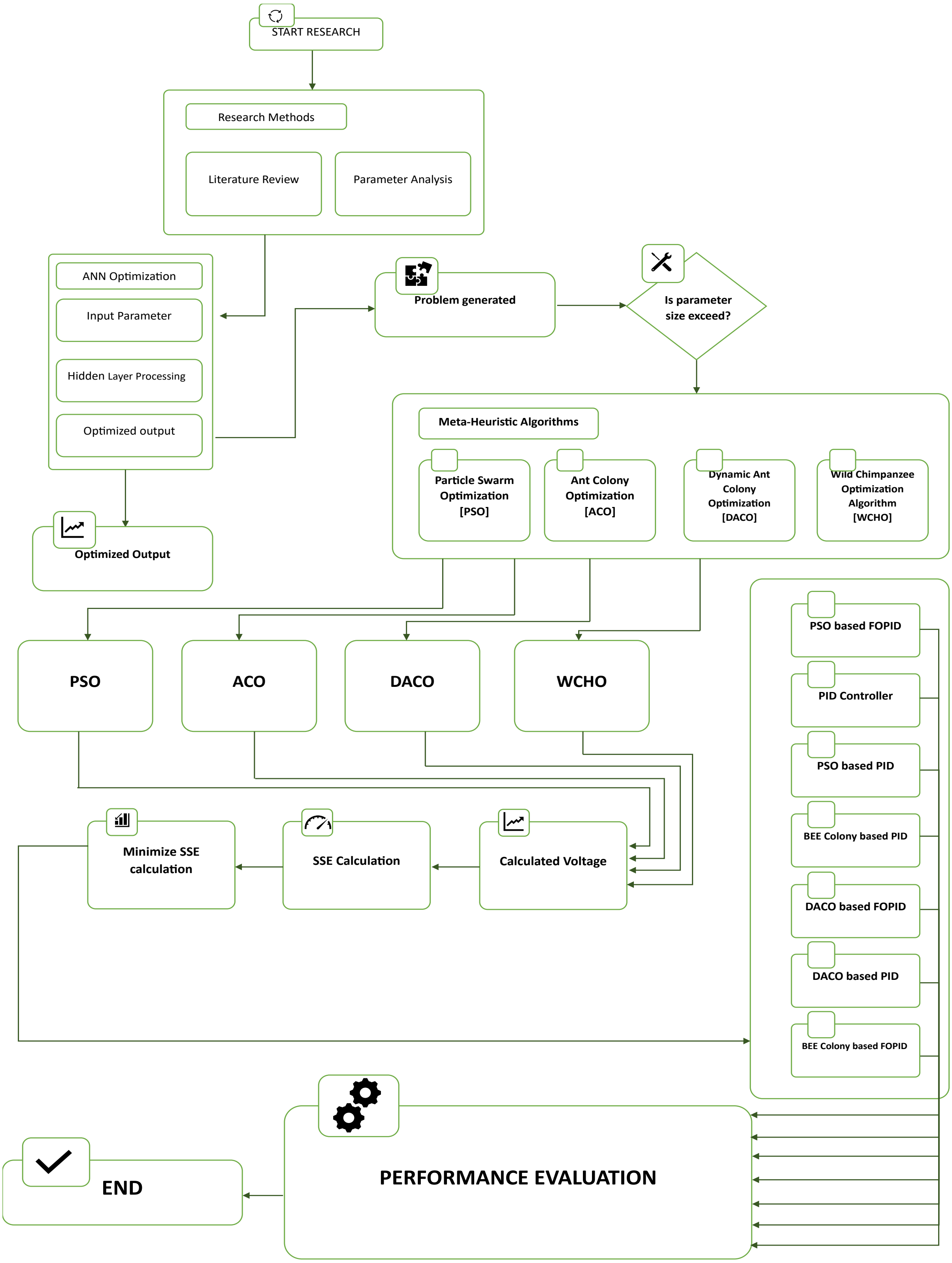

Figure 7.1 Flowchart of research work on PEMFC optimization

In this work, it can be found that the mathematical modelling using ANN and subsequent incorporation of DACO and WHCO has significantly helps to improve the PEMFC parametric optimization. It is also established that the developed novel metaheuristic algorithms i.e. DAC and WHCO successfully reduced the SSE and computational time in PEMFC parametric optimization for the OCV. The figure 7.1 shows the details work flow for this study. The step-wise work flow shows that the initially artificial neural networks (ANNs) and meta-heuristic algorithms are used for the optimization of Proton Exchange Membrane Fuel Cells (PEMFCs). The application of ANN-based multi-objective optimization presents a data-driven approach for predicting PEMFC performance under varying operational conditions. The study effectively establishes a relationship between important input parameters including temperature, relative humidity, and stoichiometry and their related effects on fuel cell efficiency and power output by training an ANN model using real-world experimental data. The ANN model, utilizing back-propagation algorithms like Levenberg-Marquardt, demonstrates high accuracy in predicting fuel cell behaviour, as indicated by a strong coefficient of determination (R^2) approx. 0.98. The output of the ANN model shows that the optimized OCV is around 0.8V which is lower than the theoretical OCV. However, this model provides an effective strategy for optimizing fuel cell operating condition which can be used for further studies to get maximum power output from PEMFC.

This study highlights that the parameter variations such as anode and cathode stoichiometry, hydrogen and oxygen partial pressures, and temperature fluctuations play a crucial role in determining PEMFC efficiency.

Subsequently, we have used the Dynamic Ant Colony Optimization (DACO) along with ANN to improve the optimization of PEMFC parameter by incorporating dynamic food movement principles into the Ant Colony Optimization (ACO) algorithm. The PEMFC operational voltage losses are optimized effectively using DACO. This ensures that the optimization process remains robust against fluctuations in operating conditions, minimizing the Sum Squared Errors (SSE) for voltage prediction. The voltage losses were reduced due to the use of DACO optimization techniques which improve the open-circuit voltage (OCV) of a single fuel cell increased by approximately 20% from 0.8V. The computation time for DACO was completed within 2.93 seconds. As evidenced by benchmark function evaluations, DACO outperforms as compared to traditional meta-heuristic algorithms like PSO, ABC, GWO etc.

In this study, a novel metaheuristic algorithm, termed the Wild Chimpanzee Hunting Optimization (WCHO) algorithm, was developed to further validate the model. The recorded computation time for WCHO was 3.67 seconds, which is significantly higher compared to DACO and other metaheuristic algorithms such as PSO, ABC, and GWO. By comparing the two newly developed algorithms in this study, it is clear that both DACO and WCHO optimization techniques can be effectively utilized for optimizing the operational parameters of PEMFC. However, DACO demonstrates superior performance in parameter estimation for PEMFC due to its less computational time. It can be attributed that the DACO allows multiple artificial ants to explore different solutions simultaneously, leveraging parallel computing to speed up the optimization process.

Furthermore, the developed DACO algorithm is validated using a 100V DC/DC boost converter. DACO is used here to optimized the PID controller parameters that are K_P, K_I, K_D and K_P, K_I, K_D, $\boldsymbol{\lambda}$ and $\boldsymbol{\mu}$ for FOPID controller. DACO-PID and DACO-FOPID controller performance was compared over conventional PID, PSO-PID, PSO-FOPID, ABC-PID, ABC-FOPID. Fitness function value, maximum overshoot percentage (M_P%), and settling time (T_S) are considered as performance indicator of PEMFC controller. The fitness function quantifies how closely the system's response matches the desired response. DACO based FOPID shows 78.2 present fitness function value which is better than PSO-FOPID controller performance. Using settling time (T_S) and maximum overshoot (M_P%) percent, the optimal approach was identified in the second step. DACO-FOPID exhibits 60% maximum overshoot (M_P%) value which is 10 percent less value compared to PSO-FOPID controller. It is found that settling time (T_S) is 230 sec for DACO-FOPID controller which is 20% less compared to PSO-FOPID controller. The best performance was shown by the fitness functions derived from ITAE. In details result analysis is presented in chapter 6. As per the result analysis, the suggested strategy of DACO-FOPID based controller perform better than the traditional PID controller and use less power when it has been integrated with boost DC-DC converter. The simulation results show that the PEMFC model with conventional PID and FOPID controllers, where controller parameters are tuned using PSO, ABC, ACO and DACO, has acceptable control performance. From the above analysis it can be summarized that further research can be focused on developing and applying these DACO based FOPID controller to various PEMFC systems to control hydrogen flow, air supply or oxygen flow, temperature, water and humidification management etc. Refining the DACO algorithm and incorporating additional machine learning techniques such as deep learning and reinforcement learning, researchers can further improve the accuracy and efficiency of PEMFC simulations.

In conclusion, the combination of ANN-based modelling and meta-heuristic optimization represents a transformative approach to maximizing PEMFC performance. The ability to optimize fuel cell parameters dynamically and predict their behaviour accurately will play a pivotal role in advancing fuel cell technology. This research not only enhances the understanding of PEMFC optimization but also establishes a framework for future developments in intelligent energy systems, ultimately contributing to the global shift towards sustainable and efficient power generation solutions. The future research on the optimization of PEMFC can be carried out in the following direction in line with this research work.

Future scope of this thesis:

i. **Development of Hybrid Optimization Models in PEMFC**– Future research can focus on integrating other newly developed metaheuristic algorithms with artificial neural networks (ANNs) to create hybrid models for optimizing PEMFC performance.

ii. **Real-Time Optimization Strategies in PEMFC** – Implementation of real-time optimization techniques, including adaptive and model predictive control (MPC), can enhance the dynamic efficiency of PEMFCs.

iii. **Advancements in Multi-Objective Optimization in PEMFC**– Research can explore multi-objective optimization approaches to balance fuel efficiency, cost, and durability of PEMFC systems.

iv. **Deep Learning & Reinforcement Learning** – The application of deep learning and reinforcement learning techniques can further refine the prediction and optimization of PEMFC operational conditions.

v. **Enhanced Computational Techniques** – Future advancements can focus on reducing the computational complexity of metaheuristic algorithms through parallel processing and heuristic-based reduction methods.

vi. **Integration with Renewable Energy Sources** – Future studies can explore integrating PEMFCs with solar, wind, and battery storage systems for efficient hybrid energy solutions.

vii. **Improved Water and Thermal Management** – Advanced water and heat management strategies can be developed to prevent flooding and maintain optimal PEMFC operating temperatures.

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