IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 21 August 2024, accepted 28 August 2024, date of publication 2 September 2024, date of current version 10 September 2024.

*Digital Object Identifier 10.1109/ACCESS.2024.3453594*

RESEARCH ARTICLE

# Optimal Parameter Extraction of PEM Fuel Cell Using a Hybrid Weighted Mean of Vectors and Nelder-Mead Simplex Method

**RAHUL KHAJURIA[1], (Graduate Student Member, IEEE),**
**MAHIPAL BUKYA[2], (Senior Member, IEEE),**
**RAVITA LAMBA[3], (Senior Member, IEEE),**
**AND RAJESH KUMAR[1], (Senior Member, IEEE)**
[1]Department of Electrical Engineering, Malaviya National Institute of Technology Jaipur, Jaipur, Rajasthan 302017, India
[2]Department of Electrical and Electronics Engineering, Manipal Academy of Higher Education, Manipal Institute of Technology Bengaluru, Bengaluru, Karnataka 576104, India
[3]Department of Hydro and Renewable Energy, Indian Institute of Technology Roorkee, Roorkee, Uttarakhand 247667, India

Corresponding author: Mahipal Bukya (mahipal.bukya@manipal.edu)

**ABSTRACT** Accurate modeling is an important aspect for a reliable design, control and optimization of proton exchange membrane (PEM) fuel cell. The mathematical model of PEM fuel cell involves a set of non-linear equations and is considered as multi-variate, multi-modal and non-linear optimization problem having seven unidentified parameters. This paper proposes a new hybrid approach based on weIghted meaN oF vectOrs and Nelder-Mead (INFONM) method for PEM fuel cell parameter extraction. An optimization problem is framed and a sum of squared error (SSE) based objective function is formulated between estimated and experimental voltages. The effectiveness of the developed approach is evaluated on four available benchmark fuel cell data sheets such as NedStack PS6, BCS 500 W, 250 W and Ballard Mark V fuel cell stacks. A fair comparison is presented with well-established algorithms as well as existing literature work to demonstrate the superiority of INFONM. The results reveal that hybrid approach produces better outcomes in terms of accuracy, reliability and effectiveness as compared to other algorithms. Also, the good closeness between the estimated and experimental polarization curves proves that hybrid approach accurately determines unknown parameters. The obtained value of SSE for NedStack PS6, BCS 500 W, 250 W and Ballard Mark V PEM fuel cell stacks are 1.242, 0.0111, 0.317, and 0.619 respectively whereas, the maximum values of percentage voltage deviations are −1.076%, 0.458%, 1.688%, and 2.69% respectively. Furthermore, statistical indices such as mean, minimum, standard deviation, and maximum value of SSE for hybrid approach indicate a least value among all other algorithms which elucidates hybrid approach as more robust and efficient. Additionally, the convergence curves, box plot study and non-parametric test further validate the robustness and reliability of INFONM in identifying unknown parameters of PEM fuel cell. Moreover, a sensitivity analysis considering SOBOL indicators is also presented to provide an illustration of influence of variation in extracted parameters on PEM fuel cell model.

**INDEX TERMS** PEM fuel cell, parameter extraction, polarization characteristics, Nelder-Mead, weighted mean of vector optimization, statistical analysis, sensitivity analysis.

## I. INTRODUCTION

Electrical energy demand is globally increasing with rapid changes in industrialization, civilization and economy [1]. Fossil fuels are used to fulfill this demand, but their major disadvantages like global warming, exhaustible nature, CO2

The associate editor coordinating the review of this manuscript and approving it for publication was Qiang Li.

**TABLE 1.** Specifications of different PEMFCs under study [16].

| Name of Stack | 250 W | Ballard Mark V | BCS 500 W | NedStack PS6 |
|---|---|---|---|---|
| No. of cell (N) | 24 | 35 | 32 | 65 |
| $l(\mu m)$ | 127 | 178 | 178 | 178 |
| $A(cm^2)$ | 27 | 50.6 | 64 | 240 |
| $Jmax(A/cm^2)$ | 860 | 1500 | 469 | 1200 |
| $T(K)$ | 353.15 | 343 | 333 | 343 |
| $PH_2(bar)$ | 1 | 1 | 1 | 0.5 |
| $PO_2(bar)$ | 1 | 1 | 0.2095 | 1 |

**TABLE 2.** Upper and lower bounds for unknown parameters of PEMFC [16], [17].

| Parameters | $\xi_1(V)$ | $\xi_2(V/K)$ | $\xi_3(V/K)$ | $\xi_4(V/K)$ | $\lambda$ | $b$ $(V)$ | $R_c$ $(\Omega)$ |
|---|---|---|---|---|---|---|---|
| Lower Bounds (LB) | -1.1997 | 1E-03 | 3.6E-05 | -2.6E-04 | 13 | 0.0136 | 1E-04 |
| Upper Bounds (UB) | -0.853 | 5E-03 | 9.8E-05 | -9.54E-05 | 23 | 0.5 | 8E-04 |

and harmful emissions limit their use [2], [3]. To effectively meet the growing demand for electrical energy, it is essential to utilize sustainable and environmentally friendly energy sources [4], [5]. Currently, renewable energy resources are increasingly popular and widely adopted for this purpose [2], [6]. These sources offer significant advantages, including being environmentally friendly, producing minimal carbon emissions, and being inexhaustible. Over the past two decades, fuel cells, a renewable energy technology, have garnered considerable interest due to their environmentally friendly operation and high efficiency [7], [8]. Fuel cell stands out as an efficient and potential technology for power generation which is being adopted for both small and large scale applications [9], [10]. Different types of available fuel cells are phosphoric acid, molten carbonate, polymer exchange membrane, solid oxide, direct methanol, alkaline and reversible fuel cells [11], [12]. Proton exchange membrane fuel cells (PEMFC) have been considered as the main choice due to their low temperature operation (30∘ C-100∘ C), robust nature, environment friendliness, high efficiency (40%-50%), and fast start up [13], [14]. All these properties of PEMFC make it applicable in various applications such as transportation, auxiliary power units, distributed generation, and space applications [1], [15].

Moreover, a PEMFC is recognized for its quick response and the manufacturers find it an emerging solution for electrical energy generation. However, a PEMFC is a highly non-linear system and involves many complex internal reactions. The operation of a single PEMFC involves many processes including electric charge transfer, heat transfer, electro-chemical reactions and mass transfer. Therefore, simultaneous occurrence of all these processes make PEMFC model complex and the prediction of characteristics of PEMFC is challenging [18]. To understand various processes that are involved in PEMFC performance assessment under different conditions and to optimize its design, an accurate mathematical model is required.

The mathematical model of a PEM fuel cell (PEMFC) is crucial for simulating and predicting its behavior in energy systems or other operations. This model is valuable for analyzing the performance of PEM fuel cells under different operating conditions. It can also optimize PEMFC operation in various applications, such as integration with renewable energy sources, energy management, energy storage systems, and microgrids. Additionally, the model aids in monitoring performance and ensuring the efficient control and utilization of the PEMFC in any energy system. Therefore, an accurate model that replicates real-time PEMFC operation is necessary. To achieve this, unknown parameters must be accurately identified, as these parameters significantly influence the behavior of the PEMFC. This behavior is typically observed through polarization characteristics, such as I-V and I-P curves. Amphlett [19] proposed a semi-empirical mathematical model to characterize PEMFC behavior that contains several equations representing various physical and chemical processes involved in its operation. Therefore, it is a great challenge to the researchers worldwide to develop an accurate model for PEMFC due to its highly non-linear nature. Nonetheless, the PEMFC mathematical model is considered as a complex, multi-variate and multi-modal, which makes it complex and hard to control and predict its performance at different conditions [18], [20]. Additionally, the model includes several unknown parameters that govern the performance of the PEMFC, with each parameter influencing the others. Even small variations in these parameters can significantly impact the output performance. Furthermore, manufacturer data sheets do not provide information on these specific parameters. Therefore, to develop an accurate model that enables effective online control and facilitates performance assessment under varying conditions such as different loads, temperatures, and gas flow rates an optimal parameter extraction approach is essential [9], [21].The behavior of a PEMFC is characterized by its polarization characteristics, which can be derived from a PEMFC model using a set of voltage equations. These voltage equations, which include various unknown parameters, have a significant impact on the polarization characteristics. Therefore, to accurately model a PEMFC and obtain polarization characteristics that closely match experimental results, a parameter identification approach is necessary.

Modern metaheuristic algorithms enabled researchers to identify the parameters of PEMFCs more accurately and efficiently [22], [23]. Numerous optimization techniques, such as lightning search algorithm (LSA) [24], whale optimization algorithm (WOA) [25], grey wolf Optimisation (GWO) [26], manta rays foraging optimizer (MRFO) [27], improved evaporation rate water cycle algorithm (ERWCA) [28], gravitational search algorithm (GSA) [29], grasshoper optimizer (GHO) [30], vortex search algorithm [31], genetic algorithm (GA), salp swarm algorithm (SSA) [32], seeker optimization algorithm (SOA) [33], pathfinder algorithm (PFA), sine tree seed algorithm (STSA), tree-seed algorithm (TSA) [34], artificial hummingbird algorithm (AHA) [35], transient search optimization (TSO) [36], honey badger algorithm (HBA) [37], firefly optimization algorithm (FOA), imperialist competitive algorithm (ICA) [38], jellyfish search algorithm (JSA) [39], shark smell optimizer (SSO) [15], teaching learning based optimizer and differential evolution (TLBO-DE) [40] etc. have been suggested by researchers in order to precisely predict the PEMFC unknown parameters. These algorithms offer several advantages, such as effectively handling non-linearities, providing faster and more accurate parameter estimation, and enabling a feature selection mechanism for improved performance. Their use has allowed researchers to obtain PEMFC parameters with greater accuracy, resulting in more precise predictions and enhanced performance. Moreover, the No Free Lunch (NFL) theorem clarifies that no single optimization algorithm can deliver an equally effective and accurate solution for every optimization problem [17]. While each of these meta-heuristic optimization algorithms can be applied to extract unknown PEMFC parameters, their performance may vary significantly depending on their designed search strategies. Moreover, relying solely on metaheuristic algorithms may not yield satisfactory results for achieving an accurate model. Therefore, combining a metaheuristic algorithm with a traditional optimization approach is an effective way to enhance performance and achieve more accurate and optimal results.

The above discussion inspires the authors to hybridize a recently developed metaheuristic optimization technique called INFO with Nelder Mead simplex method and formulate an effective INFONM method for identifying accurate values of PEMFC model unknown parameters. To the authors' best of knowledge, this is the first time, INFONM is employed to obtain the optimal parameters of PEMFC. The main goal of this paper is to develop a realistic and accurate model of PEMFC that provides precise modeling and simulation results in obtaining non-linear PEMFC I-V characteristics including unknown parameters. In this context, a hybrid INFONM approach is proposed for PEMFC parameter extraction to determine the values of unknown parameters. This approach minimizes the deviation between experimental and estimated polarization characteristics, thereby helping to obtain an accurate PEMFC model by predicting the optimal values of unknown variables. Moreover, it converges rapidly to a solution and is reliable and robust in solving parameter extraction problems under various scenarios. In this work, the parameter extraction problem is first formulated mathematically as a non-linear optimization problem, with an SSE based objective function defined between the experimental and estimated voltages. A high level of correlation is achieved between the polarization curve obtained through the optimization method and the experimental data. To demonstrate the superiority of INFONM, a fair comparison is made between INFONM and other algorithms such as grey wolf optimization (GWO), bald eagle search (BES), whale optimization algorithm (WOA), weighted mean of vectors (INFO) in identifying parameters. Four commercially available data sheets of PEMFC stacks are studied, and results based on statistical analysis, voltage deviation, and non-parametric tests are evaluated to confirm the effectiveness and reliability of the developed approach compared to other algorithms. Box plot and convergence curve analyses are presented to demonstrate the robustness and convergence speed of INFONM relative to other algorithms. Additionally, sensitivity analysis based on the SOBOL indicator is provided to illustrate the influence of variations in extracted parameters on the PEM fuel cell model. The main contributions of this paper are as follows:

- Proposing a new hybrid INFONM algorithm based on global and local search capability of INFO and NM algorithm.
- Evaluating the effectiveness and reliability of INFONM in terms of accuracy in identification of polarization characteristics.
- Implementing proposed approach on four well known PEMFC stacks and comparing its performance with other metaheuristic algorithms based on convergence speed, statistical analysis, and box plot analysis to prove its superiority.
- Evaluating the performance of INFONM at different scenarios of temperatures and pressures.
- Performing sensitivity analysis to examine the effect of variation of extracted parameters on PEMFC model.

The organization of this paper is as follows: Section II describes the mathematical modeling of PEM fuel cell. Problem formulation is defined in Section III. Section IV describes the INFO and Nelder Mead methods as methodology used in this paper and Section V gives a detailed analysis about the results obtained in identifying unknown parameters of different PEMFC stack under consideration. Then, Section VI concludes the paper.

## II. MATHEMATICAL MODELING OF PEM FUEL CELL

A PEM fuel cell converts the chemical energy of reactants into electricity. It consists of two electrodes, the anode and the cathode, which facilitate the supply of reactants and allow the flow of electrons to the external circuit. A polymer electrolyte membrane is situated between these electrodes, permitting the flow of protons while preventing electrons from passing through it. Since a single fuel cell cannot deliver a high power output, multiple fuel cells are connected in series to form a fuel cell stack [44]. The behavior of a fuel cell is described by its polarization characteristics, which are obtained from a set of voltage equations. These characteristics include the current-voltage (I-V) and current-power (I-P) relationships of the fuel cell. To simulate these characteristics, a PEM fuel cell is represented by a mathematical model. This model comprises a set of voltage equations used to determine the total output voltage. The detailed mathematical model, incorporating these equations, is described as follows:

The value of the output stack voltage ($V_{stac}$) can be expressed as [45]:

$$V_{stac} = N_{cell}\left[E_{ner} - V_{act} - V_{ohm} - V_{con}\right] \tag{1}$$

**TABLE 3.** Results obtained from INFONM and other algorithms for 250 W PEMFC Stack.

| Algorithm | GWO | BES | JAYA | WOA | INFO | HBA [39] | JSA [41] | IAEO [43] | AHA [37] | IAHA [37] | GOA [32] | INFO NM |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $\xi_1(V)$ | -1.0457E+00 | -8.6332E-01 | -1.1882E+00 | -9.7418E-01 | -1.0669E+00 | - 0.9486 | -9.6089E-01 | -8.7700E-01 | -9.6140E-01 | -1.0866E+00 | 0.8532 | -9.4877E-01 |
| $\xi_2(V/K)$ | 2.8565E-03 | 2.2034E-03 | 3.8634E-03 | 2.6115E-03 | 3.4953E-03 | 3.25E-03 | 3.2200E-03 | 2.8000E-03 | 3.2 E-03 | 3.3 E-03 | 3.1237 E-03 | 4.4438E-03 |
| $\xi_3(V/K)$ | 4.1086E-05 | 3.6001E-05 | 8.0731E-05 | 3.6032E-05 | 7.9889E-05 | 7.80E-5 | 8.1100E-05 | 6.9200E-05 | 6.7700E-05 | 5.1000E-05 | 9.8000E+00 | 8.9752E-05 |
| $\xi_4(V/K)$ | -1.4622E-04 | -1.0941E-04 | -1.6564E-04 | -1.7680E-04 | -1.7203E-04 | -7.80E-5 | -1.7500E-04 | -6.9200E-05 | 1.75E-04 | -1.7500E-04 | 17.0112E-04 | -1.6862E-04 |
| $\lambda$ | 1.8640E+01 | 1.4496E+01 | 1.4107E+01 | 1.5751E+01 | 1.5837E+01 | 1.7E-01 | 1.99358 E+01 | 2.15177 E+01 | 1.98974 E+01 | 1.99358 E+01 | 1.8344E+01 | 1.4795E+01 |
| $b(V)$ | 2.9474E-02 | 2.7811E-02 | 1.3600E-02 | 1.5528E-02 | 1.4017E-02 | 1.6000E-02 | 1.45265 E-02 | 1.5 E-02 | 1.4457 E-02 | 1.4527 E-02 | 1.3600E-02 | 2.8075E-01 |
| $R_c$ ($\Omega$) | 5.2031E-04 | 2.9623E-04 | 4.5256E-04 | 2.4294E-04 | 7.0623E-04 | 8.0E-04 | 1.0000E-04 | 2.7300E-04 | 1.0300E-04 | 1.0000E-04 | 1.0000E-04 | 6.5462E-04 |
| SSE | 0.332245 | 0.331375 | 0.332421 | 0.331471 | 0.331373 | 0.354 | 0.335980 | 0.335900 | 0.336004 | 0.335980 | 0.339500 | **0.316798** |

**TABLE 4.** Results obtained from INFONM and other algorithms for ballard mark V PEMFC stack.

| Algorithm | GWO | BES | JAYA | WOA | INFO | GOA [32] | PFA [36] | NNO [44] | AHA [37] | TSO [38] | GHO [32] | INFONM |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $\xi_1(V)$ | -1.1501E+00 | -8.5323E-01 | -1.1997E+00 | -1.1540E+00 | -8.6408E-01 | -0.8532 | -1.1997E+00 | -9.7997E-01 | -1.1417E+00 | -8.7416E-01 | 0.8532 | -1.1869E+00 |
| $\xi_2(V/K)$ | 4.0360E-03 | 2.5604E-03 | 4.0115E-03 | 3.4047E-03 | 3.3264E-03 | 3.4173E-03 | 3.95786 E-03 | 3.69460 E-03 | 4.2 E-03 | 3.084361 E-03 | 3.4173E-03 | 2.6931E-03 |
| $\xi_3(V/K)$ | 8.2998E-05 | 3.6133E-05 | 6.7885E-05 | 3.6350E-05 | 9.0436E-05 | 9.80E-05 | 6.3901 E-05 | 9.08710 E-05 | 7.8700E-05 | 7.96 E-05 | 9.8000E-05 | 4.9463E-05 |
| $\xi_4$ (V/K) | -1.4434E-04 | -1.6313E-04 | -1.6119E-04 | -1.4829E-04 | -1.5050E-04 | -1.59555E-04 | -1.6300E-04 | -1.62820 E-04 | -1.6300E-04 | -9.77 E-04 | 15.9555E-05 | -2.5110E-04 |
| $\lambda$ | 2.2846E+01 | 2.2999E+01 | 2.2814E+01 | 2.3000E+01 | 2.3000E+01 | 2.28458 E+01 | 2.3000 E+01 | 2.3000 E+01 | 2.3000 E+01 | 2.27134 E+01 | 2.2846E+01 | 2.0743E+01 |
| $b(V)$ | 1.3677E-02 | 1.3600E-02 | 1.3600E-02 | 1.3732E-02 | 1.3600E-02 | 1.36E-02 | 1.3600E-02 | 1.3600E-02 | 1.36 E-02 | 1.36 E-02 | 1.3600E-02 | 5.1452E-02 |
| $R_c$ ($\Omega$) | 2.4933E-04 | 1.0006E-04 | 1.0649E-04 | 2.3140E-04 | 2.6107E-04 | 1.00 E-04 | 1.00 E-04 | 1.0000 E-04 | 1.0000E-04 | 7.636 E-04 | 1.0000E-04 | 3.4860E-04 |
| SSE | 0.862466 | 0.912729 | 0.879791 | 0.853608 | 0.853608 | 0.8710 | 0.853610 | 0.853610 | 0.853621 | 1.721000 | 0.871000 | **0.619895** |

**TABLE 5.** Results obtained from INFONM and other algorithms for BCS 500 W PEMFC stack.

| Algorithm | GWO | BES | JAYA | WOA | INFO | SSO [34] | HBA [39] | FOA [45] | ICA [45] | JSA [41] | AHA [37] | INFONM |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $\xi_1(V)$ | -9.2916E-01 | -1.0598E+00 | -1.1936E+00 | -1.1997E+00 | -1.1639E+00 | -0.8532 | -0.952 | -0.992829 | -0.908643 | -0.96887 | -1.0497 | -1.1230E+00 |
| $\xi_2(V/K)$ | 3.1708E-03 | 3.1696E-03 | 3.2103E-03 | 3.7236E-03 | 3.1461E-03 | 4.8115 E-03 | 3.20E-03 | 2.621 E-03 | 2.4798 E-03 | 2.69E-03 | 2.9 E-05 | 3.4501E-03 |
| $\xi_3(V/K)$ | 8.5319E-05 | 5.9936E-05 | 3.6932E-05 | 6.8437E-05 | 3.8135E-05 | 9.4334 E-05 | 7.40E-05 | 3.746368 | 4.4583194 | 4.67E-05 | 3.84E-05 | 6.5693E-05 |
| $\xi_4(V/K)$ | -1.8642E-04 | -1.8978E-04 | -1.8853E-04 | -1.9214E-04 | -1.9366E-04 | -1.9205 | -7.24E-05 | -1.93 | -1.93 | -1.90E-04 | -1.93E-04 | -1.9481E-04 |
| $\lambda$ | 1.8345E+01 | 2.0141E+01 | 2.2626E+01 | 2.1585E+01 | 2.1930E+01 | 2.3E+01 | 2.01E+01 | 21.101126 | 22.66264 | 20.8389 | 22.0516 | 1.3822E+01 |
| $b(V)$ | 1.4861E-02 | 1.5794E-02 | 1.6178E-02 | 1.5846E-02 | 1.6671E-02 | 1.589 E-02 | 1.60E-02 | 1.6269 E-02 | 1.6238 E-02 | 1.6111 E-02 | 1.636 E-02 | 1.5326E-02 |
| $R_c$ ($\Omega$) | 2.0264E-04 | 1.7736E-04 | 3.2431E-04 | 2.2741E-04 | 1.2309E-04 | 3.499 E-04 | 5.43E-04 | 1.00 E-04 | 2.46 E-04 | 1.00 E-04 | 1.80E-04 | 1.7736E-04 |
| SSE | 0.01409845 | 0.01204918 | 0.03456726 | 0.01225302 | 0.01207378 | 0.01219535 | 0.01186854 | 0.01181924 | 0.01185645 | 0.01169945 | 0.01183125 | **0.01110012** |

**TABLE 6.** Results obtained from INFONM and other algorithms for NedStack PS6 PEMFC stack.

| Algorithm | GWO | BES | JAYA | WOA | INFO | GSA [31] | VSA [33] | GA [32] | SSA [43] | MRFO [29] [45] | INFONM |
|---|---|---|---|---|---|---|---|---|---|---|---|
| $\xi_1(V)$ | -8.7188E-01 | -8.5320E-01 | -8.5320E-01 | -9.7297E-01 | -8.5368E-01 | -8.7387E-01 | -8.9460E-01 | 1.1997 | -9.8940E-01 | -1.0560E+00 | -8.5496E-01 |
| $\xi_2(V/K)$ | 2.6584E-03 | 2.3988E-03 | 3.0560E-03 | 3.6153E-03 | 2.3997E-03 | 3.3487 E-03 | 3.3500E-03 | 3.4172 E-03 | 3.3300E-03 | 3.13 E-03 | 2.4558E-03 |
| $\xi_3(V/K)$ | 5.0484E-05 | 3.6000E-05 | 8.2977E-05 | 9.8000E-05 | 3.6000E-05 | 8.9300E-05 | 9.7500E-05 | 3.6 E-05 | 7.4100E-05 | 4.6100E-05 | 3.9676E-05 |
| $\xi_4(V/K)$ | -9.5400E-05 | -9.5400E-05 | -9.5400E-05 | -9.5400E-05 | -9.5400E-05 | -9.5400E-05 | -9.5400E-05 | -9.5400E-05 | -9.5400E-05 | 9.580E-05 | -9.5401E-05 |
| $\lambda$ | 1.3292E+01 | 1.3000E+01 | 1.3000E+01 | 1.3000E+01 | 1.3000E+01 | 1.8800E+01 | 1.3000E+01 | 1.3 E+01 | 2.05477 E+01 | 2.0188E+01 | 1.3001E+01 |
| $b(V)$ | 6.4067E-02 | 5.1883E-02 | 5.2341E-02 | 5.2056E-02 | 4.8833E-02 | 5.65881 E-02 | 1.0300E-02 | 1.376 E-02 | 2.5600E-02 | 5.4700E-02 | 3.2045E-02 |
| $R_c$ ($\Omega$) | 1.1947E-04 | 1.0000E-04 | 1.0000E-04 | 1.0000E-04 | 1.0141E-04 | 2.388 E-04 | 4.29 E-04 | 3.59 E-04 | 4.2600 E-04 | 1.6600 E04 | 1.1900E-04 |
| SSE | 2.3715323 | 2.3142578 | 2.3122852 | 2.3035537 | 2.3035537 | 2.5827000 | 2.3426000 | 2.4089000 | 2.5711000 | 2.8870200 | **1.2424162** |

where, $N_{cell}$ represents the number of cells, $E_{ner}$, $V_{act}$, $V_{ohm}$, and $V_{con}$ represent reversible voltage, activation voltage losses, ohmic voltage drop, concentration voltage losses, respectively in volts. The first term in the right hand side of Equation (1) represents the nernst voltage that is the potential of the fuel cell at no load, whereas, the other three terms represent the activation, ohmic and concentration voltage drops that reduces the total output voltage with the increase in fuel cell current. The mathematical calculations for obtaining Nernst reversible voltage $E_{ner}$, also called as thermodynamic open circuit voltage, can be obtained from the basic Nernst equation which is expressed as follows [46] and [47]:

$$\begin{aligned} E_{ner} = 1.229 - 0.85 * 10^{-03}\left[T_{fc} - 298.15\right] \\ + 4.3085 * 10^{-05} * T_{fc}\left[\ln\left(PH_2 + \sqrt{PO_2}\right)\right] \end{aligned} \tag{2}$$

where, $T_{fc}$ is operating temperature in $K$. $PH_2$ and $PO_2$ are hydrogen and oxygen pressures respectively in bar.

The activation potential drop results from the process of activation occurring around the cathode and anode of the fuel cell. This potential drop is given as [48]:

$$V_{act} = -\left[\xi_1 + \xi_2 * T + \xi_3 * T_{fc} * ln\left(C_{O2}\right) + \xi_4 * T_{fc} * ln\left(I_{fc}\right)\right] \tag{3}$$

where, $\xi_1$ (V), $\xi_2$ (V/K), $\xi_3$ (V/K), and $\xi_4$ (V/K) are semi-empirical coefficients and $C_{O2}$ represents the concentration of oxygen. The concentration of oxygen can be calculated from the following equation [48]:

$$C_{O2} = \frac{PO_2}{5.08 \times 10^6 \times exp\left(\frac{T_{fc}}{498}\right)} \tag{4}$$

The ohmic potential drop occurs due to the resistance that hinders the flow of electrons in fuel cell. This drop results a linear decrease in fuel cell voltage and is given as [48]:

$$V_{ohm} = I_{fc}\left[R_m + R_c\right] \tag{5}$$

where, $R_m$ and $R_c$ represent electronic and ionic resistances, respectively. The value of electronic resistance can be

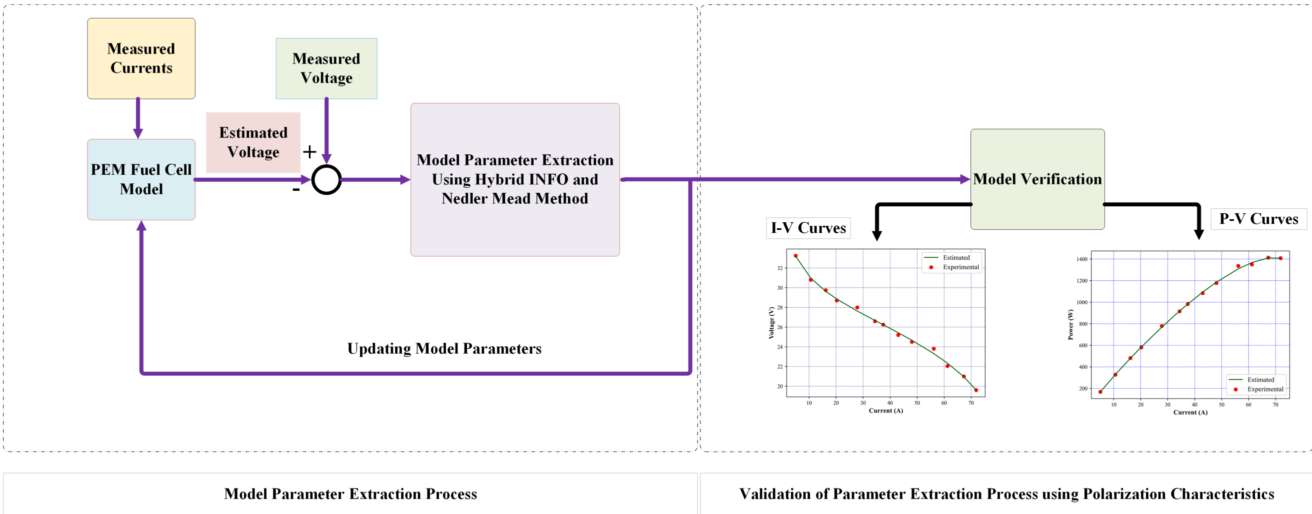



**FIGURE 1.** **PEM fuel cell parameter extraction process using INFONM algorithm.**

obtained using following equation [48]:

$$R_m = \rho_m \left(\frac{l}{A}\right) \tag{6}$$

where, $\rho_m$ represents specific resistivity in $\Omega cm$, $l$ represents length of membrane in $\mu m$ and $A$ represents area in $cm^2$. The specific resistivity is obtained as [48]:

$$\rho_m = \frac{181.6\left[1+0.03\left(\frac{I_{fc}}{A}\right)+0.062\left(\frac{I_{fc}}{A303}\right)^2\left(\frac{T_{fc}}{A}\right)^{2.5}\right]}{\left[\lambda-0.634-3\left(\frac{I_{fc}}{A}\right)\right]\times exp\left(\frac{4.18(T_{fc}-303)}{T_{fc}}\right)} \tag{7}$$

where, $\lambda$ represents adjustable parameter and $\rho_m$ represents the specific resistivity in $\Omega cm$.

The concentration potential drop occurs due to mass transfer of fuel cell reactants. This results in a non-linear reduction of fuel cell voltage at high current densities. The concentration voltage drop is obtained using the following equation [48]

$$V_{con} = -b * ln\left[1-\frac{J}{J_{max}}\right] \tag{8}$$

where, $b$ represents the parametric coefficient (V), $J$ and $J_{max}$ are the actual and maximum current densities, respectively in $A/cm^2$. From above equations (1)-(11), it is observed that $\xi_1, \xi_2, \xi_3, \xi_4, \lambda, b$, and $R_C$ are unknown parameters. These parameters are mentioned in the manufacturer's data sheet. Consequently, it is observed that in obtaining an accurate PEMFC model, these parameters are needed to identify optimally. Therefore, in this work, a parameter extraction process based on hybrid INFONM algorithm is proposed and unidentified parameters are extracted effectively. The problem formulation and methodology adopted in obtaining these parameters is discussed in next sections.

## III. PROBLEM FORMULATION

The major limitations in developing an accurate PEMFC model are (i) there is no information of several parameters that are used in mathematical model on fuel cell data sheets (ii) any small variation in the values of these parameters greatly influence the polarization characteristics and (iii) any inaccurate value of these parameters can largely deviate the simulated polarization characteristics from actual one. Therefore, to build an accurate PEMFC model considering equations (1)-(11), the values of parameters like $\xi_1, \xi_2, \xi_3, \xi_4, \lambda, b$, and $R_C$ should be accurately estimated. Also, the parameter extraction process for PEMFC is considered as a highly non-linear, multivariate and challenging task. Therefore, to solve this problem, an objective function is required to minimize the deviations between the estimated and experimental results. An objective function, formulated as an SSE between the experimental and estimated voltage values of the PEMFC model is defined as follows:

$$F_{obj} = SSE = \sum_{i=1}^{N}\left(V_{j,exp.} - V_{j,est.}\left\{X, I_{fc}\right\}\right)^2 \tag{9}$$

where, $F_{obj}$ represents the objective function. $V_{j,est.}$ and $V_{j,exp.}$ represent estimated and experimental voltage values. $X$ represents the set of unknown parameters that need to be identified optimally. A set of inequality constraints for the given objective function are as follows:

$$S.t \begin{cases} \xi_{i,LB} \leq \xi_i \leq \xi_{i,UB} \forall_i \in \{1,2,3,4\} \\ \lambda_{LB} \leq \lambda \leq \lambda_{UB} \\ b_{LB} \leq b \leq b_{UB} \\ R_{c,LB} \leq R_c \leq R_{c,UB} \end{cases} \tag{10}$$

To address the PEM fuel cell parameter extraction problem, a voltage-based objective function is defined in Equation (9). This objective function represents the sum of squared errors (SSE) between experimental voltage data points and estimated voltage data points. It quantifies the closeness between the estimated and experimental voltage points by calculating the squared error between the polarization characteristics. Experimental voltage data points are those measured from experiments, while estimated voltage data points are the results obtained from estimating PEM fuel cell parameters using an optimization approach. A lower SSE value indicates a closer match between the experimental and estimated polarization characteristics, leading to a more accurate mathematical model. Therefore, the effectiveness of developing an accurate PEMFC model relies on minimizing the SSE objective function. In this study, the INFONM algorithm is proposed as the optimization approach to solve the PEMFC parameter extraction problem, with SSE as the objective function. The primary aim is to minimize SSE to obtain the optimal parameter values, ensuring that the estimated polarization characteristics closely match the experimental ones and result in a more accurate model.

## IV. METHODOLOGY

In this paper, a hybrid algorithm, based on WeIghted meaN oF VectOrs (INFO) and nelder mead (NM) called as INFONM is proposed in identifying the unknown parameters. The types of algorithms that are employed at each step of the search process are unlimited and any algorithm with a qualifying feature at that stage can be adopted. Thus, the characteristics of different algorithms can be combined and a hybridized algorithm can be formulated to achieve better results [49]. INFONM consists of two stages for searching, global search and local search. The main purpose of the first stage is to explore the search space globally for finding a solution whereas, the second stage involves an intensive local search based on solutions obtained in the first stage. Therefore, this study proposes an INFONM algorithm for the process of PEMFC parameter extraction based on INFO as a global exploration algorithm and NM algorithm for intensive exploitation. The detailed mathematical formulation of these algorithms are explained as follows:

### A. WEIGHTED MEAN OF VECTORS (INFO) ALGORITHM

INFO algorithm uses weighted mean and position of vector is updated using three operators which are updating rule, vector combining and local search. In this algorithm, optimal solution is obtained using these three operations over successive generations. In this subsection, firstly the mathematical definition of weighted mean is described which is average of populations ($p_i$) as weighted by fitness of vector ($w_i$). The weighted mean is defined as follows [50]:

$$WM = \frac{\sum_{i=1}^{N} p_i \times w_i}{\sum_{i=1}^{N} w_i} \tag{11}$$

where, $N$ represents number of vectors. For better explanation, consider three vectors $p_1$, $p_2$, and $p_3$, $WM$ is given as follows:

$$WM = \frac{w_1(p_1 - p_2) + w_2(p_1 - p_3) + w_3(p_2 - p_3)}{w_1 + w_2 + w_3} \tag{12}$$

$$w_1 = \cos\left((f(p_1) - f(p_2)) + \pi\right) \times \exp\left(-\left|\frac{f(p_1) - f(p_2)}{\omega}\right|\right) \tag{13}$$

$$w_2 = \cos\left((f(p_1) - f(p_3)) + \pi\right) \times \exp\left(-\left|\frac{f(p_1) - f(p_3)}{\omega}\right|\right) \tag{14}$$

$$w_3 = \cos\left((f(p_2) - f(p_3)) + \pi\right) \times \exp\left(-\left|\frac{f(p_2) - f(p_3)}{\omega}\right|\right) \tag{15}$$

where, $f(p)$ represent the fitness function of vector $p$. $w$ represents the mother wavelet function to obtain effective oscillation during optimization. Mother wavelet function is defined as follows:

$$w = cos(p) \times exp\left(-\frac{p^2}{\omega}\right) \tag{16}$$

where, $\omega$ represent a constant number and is called as dilation parameter. The main formulation of algorithm considering populations as a set of vectors is as follows:

*Initialization:*

$$P_{l,j}^{g} = p_{l,1}^{g}, p_{l,2}^{g}, \ldots, p_{l,D}^{g} \tag{17}$$

where, $l = 1, 2 \ldots, N_p$

*Updating Rule:* In this stage *MeanRule* based on top five solutions is considered and is evaluated as follows:

$$MeanRule = r \times WM1_l^g + (1 - r) \times WM2_l^g \tag{18}$$

**Algorithm 1** INFO

**Initialization**: $P_{l,j}^{g} = p_{l,1}^{g}, p_{l,2}^{g}, \ldots, p_{l,D}^{g}$.
Objective function evaluation for each vector $f(P_{l,j}^{g})$ and determine best vector $p_{bs}$
**for** $g = 1$ to Maxg **do**
  **for** $i = 1$ to $N_p$ **do** Randomly select $a \neq b \neq c \neq i$ in the range $[1, N_p]$
    **Updating rule stage:** Determine the vectors $z1_l^g$ and $z2_i^g$ using Equation (32)-(38)
    **Vector Updating stage:** Determine the vector $u_i^g$ using Equation (39)-(41)
    **Local search stage:** Determine the operator for local search using Equation 42-45 and evaluate the objective function $f(u_{i,j}^{g})$
    **if** $f(u_{i,j}^{g}) < f(p_{i,j}^{g})$ **then** $p_{i,j}^{g+1} = u_{i,j}^{g}$
    **else** $p_{i,j}^{g+1} = p_{i,j}^{g}$
    **end if**
  **end for**
  Update the best vector $p_{bs}$
**end for**
**return** Vector $p_{best,j}^{g}$ as the final solution

where,

$$WM1_l^g = \delta \times \frac{w_1 (p_{a1} - p_{a2}) + w_2 (p_{a1} - p_{a3}) + w_3 (p_{a2} - p_{a3})}{w_1 + w_2 + w_3 + \varepsilon + \varepsilon \times \text{ rand}} \tag{19}$$

where,

$$w_1 = \cos((f(p_{a1}) - f(p_{a2})) + \pi) \times \exp\left(-\left|\frac{f(p_{a1}) - f(p_{a2})}{\omega}\right|\right) \tag{20}$$

$$w_2 = \cos((f(p_{a1}) - f(p_{a3})) + \pi) \times \exp\left(-\left|\frac{f(p_{a1}) - f(p_{a3})}{\omega}\right|\right) \tag{21}$$

$$w_3 = \cos((f(p_{a2}) - f(p_{a3})) + \pi) \times \exp\left(-\left|\frac{f(p_{a2}) - f(p_{a3})}{\omega}\right|\right) \tag{22}$$

$$\omega = \max(f(p_{a1}), f(p_{a2}), f(p_{a3})) \tag{23}$$

$$WM2_l^g = \delta \times \frac{w_1 (p_{bs} - p_{bt}) + w_2 (p_{bs} - p_{ws}) + w_3 (p_{bt} - p_{ws})}{w_1 + w_2 + w_3 + \varepsilon + \varepsilon \times rand} \tag{24}$$

where,

$$w_1 = \cos((f(p_{bs}) - f(p_{bt})) + \pi) \times \exp\left(-\left|\frac{f(p_{bs}) - f(p_{bt})}{\omega}\right|\right) \tag{25}$$

$$w_2 = \cos((f(p_{bs}) - f(p_{ws})) + \pi) \times \exp\left(-\left|\frac{f(p_{bs}) - f(p_{ws})}{\omega}\right|\right) \tag{26}$$

$$w_3 = \cos((f(p_{bt}) - f(p_{ws})) + \pi) \times \exp\left(-\left|\frac{f(p_{bt}) - f(p_{ws})}{\omega}\right|\right) \tag{27}$$

$$\omega = f(p_{ws}) \tag{28}$$

where, $\epsilon$ represents a constant number with very small value. $p_{bt}$, $p_{bs}$, and $p_{ws}$ represent better, best, and worst solutions. $a_1 \neq a_2 \neq a_3 \neq l$ represent different randomly selected integers in range $[1, N_p]$. $r$ represent a random number between 0 and 0.5. *rand* represents a random value.

$$\delta = 2\beta \times rand - \beta \tag{29}$$

$$\beta = 2 * exp\left(-4 \times \frac{g}{Maxg}\right) \tag{30}$$

The global search ability of algorithm is enhanced using a convergence acceleration ($CA$) and is added to updating rule. The mathematical formulation is given as follows:

$$CA = randn \frac{(p_{bs} - p_{a1})}{f(p_{bs}) - f(p_{a1} + \epsilon)} \tag{31}$$

where *randn* represents a normally distributed random value. Finally new vector is evaluated as follows:

$$z_g^l = x_g^l + \sigma \times MeanRule + CA \tag{32}$$

**Algorithm 2** Nelder-Mead Simplex Method

Formulate a simplex of D+1 vertices.
Set parameters $\alpha = 1, \gamma = \delta = 0.5, \beta = 2, Iteratins = 1000$.
**Step:1** Sort in ascending order as $f(p_1) < f(p_2) < \ldots < f(D) < f(D+1)$.
**Step:2** Evaluate Reflection Point, $p_r = (1+\alpha)\overline{\mathrm{p}} - \alpha p_{D+1}$.
**if** $f(p_1) \leq f(p_r) \leq f(p_D)$ **then** Replace $p_{D+1}$ with $p_r$ and Go to Step 6.
    **if** $f(p_r) \leq f(p_1)$ **then** Move to Step 3.
        **if** $f(p_r) \geq f(p_1)$ **then** Go to Step 4.
        **end if**
    **end if**
**end if**
**Step:3** Evaluate Expansion Pont, $p_e = (1-\beta) \cdot \overline{\mathrm{p}} + \beta p_r$.
**if** $f(p_e) \leq f(p_r)$ **then**.
    Replace $p_{D+1}$ with $p_e$.
**else**
    Replace $p_{D+1}$ with $p_r$ and Move to Step 6.
**end if**
**Step:4**
**if** $f(p_r) < f(p_{D+1})$ **then**, evaluate outside contraction point $p_{oc}$ using Equation (49).
**else**
    Evaluate inside contraction point using Equation (50).
**end if**
**Step:5** Except $p_i$ Shrink all vertices using Equation (51).
**Step:6** Check end criterion.
**if** Condition is met **then** Stop the search.
**else**
    Begin the subsequent iteration using the updated simplex.
**end if**

*if rand* $\leq 0.5$:

$$z1_g^l = p_g^l + \sigma \times MeanRule + randn \times \frac{(p_{bs} - p_{a1}^g)}{(f(p_{bs}) - f(p_{a1}^g) + 1)} \tag{33}$$

$$z2_l^g = p_{bs} + \sigma \times MeanRule + randn \times \frac{(p_{a1}^g - p_b^g)}{(f(p_{a1}^g) - f(p_{a2}^g) + 1)} \tag{34}$$

*else*

$$z1_l^g = p_a^g + \sigma \times MeanRule + randn \times \frac{(p_{a2}^g - p_{a3}^g)}{(f(p_{a2}^g) - f(p_{a3}^g) + 1)} \tag{35}$$

$$z2_l^g = p_{bt} + \sigma \times MeanRule + randn \times \frac{(p_{a1}^g - p_{a2}^g)}{(f(p_{a1}^g) - f(p_{a2}^g) + 1)} \tag{36}$$

$$\sigma = 2\alpha \times \text{ rand } - \alpha \tag{37}$$

$$\alpha = c * exp\left(-d \times \frac{g}{Maxg}\right) \tag{38}$$

*Vector Combining Stage:* To improve the diversity in population, calculated vectors in previous stage are combined as follows:

***if*** *rand* $\leq 0.5$

$$u_l^g = z1_l^g + \mu.\left|z1_l^g - z2_l^g\right| \tag{39}$$

***else***

$$u_l^g = z2_l^g + \mu.\left|z1_l^g - z2_l^g\right| \tag{40}$$

***end***

***else***

$$u_l^g = p_l^g \tag{41}$$

***end***

where, $u_l^g$ represents vector found in combining stage and $\mu = 0.05 \times randn$

*Local Search Stage:* To avoid being trapped in local minima an effective local search helps in obtaining the optimal solution. This can be defined as follows: if *rand* $\leq 0.5$

$$u_l^g = p_{bs} + randn \times \left(MeanRule + rand \times \left(p_{bs}^g - p_{a1}^g\right)\right) \tag{42}$$

else

$$u_l^g = p_{rnd} + randn \times (MeanRule + rand \times (v_1 \times p_{bs} - v_2 \times p_{rnd})) \tag{43}$$

where,

$$p_{rnd} = \phi \times p_{avg} + (1-\phi) \times (\phi \times p_{bt} + (1-\phi) \times p_{bs})$$
$$p_{avg} = \frac{(p_a + p_b + p_3)}{3} \tag{44}$$
$$v_1 = \begin{cases} 2 \times \text{ rand} & \text{if } r > 0.5 \\ 1 & \text{otherwise} \end{cases}$$
$$v_2 = \begin{cases} \text{rand} & \text{if } r < 0.5 \\ 1 & \text{otherwise} \end{cases} \tag{45}$$

where, r is random number between 0 and 1. The pseudo code for INFO algorithm is presented as Algorithm 1.

### B. NELDER-MEAD SIMPLEX METHOD

Nelder-Mead (NM) is an iterative algorithm that does not require any gradient information to solve an optimization problem. To solve any d dimensional optimization problem NM uses D = 1 starting vertices to form a simplex, and new vertices replace the worst vertices on each iteration. It consists of four parameters which are known as expansion factor $\beta$, reflection factor $\alpha$, shrinkage factor $\delta$, and contraction factor $\gamma$. The pseudo code for NM method is represented in Algorithm 2. The iteration for NM method can be performed as follows:

*Step 1:* Sort every vertex in an ascending order and renumber them as per their fitness function values.

*Step2:* Evaluate the reflection point $p_r$ as per following equation

$$p_r = (1+\alpha)\overline{\text{p}} - \alpha p_{D+1} \tag{46}$$
$$\overline{\text{p}} = \sum_{i=1}^{n} \text{p}_i/D \tag{47}$$

if $f(p_1) \leq f(p_r) \leq f(p_D)$ then replace $p_{D+1}$ with $p_r$ and jump to Step 6; if$f(p_r) \leq f(p_1)$ then go to Step3; if $f(p_r) \geq f(p_1)$, then jump to Step 4.

*Step:3* Calculate the expansion point $p_e$ as follows:

$$p_e = (1-\beta)\overline{\text{p}} + \beta p_r \tag{48}$$

if$f\ (p_e) \leq f\ (p_r)$, then replace $p_{D+1}$ with $p_e$; else, replace $p_I$ $p_\text{r}$. Then, jump to Step 6.

*Step 4:* calculate the inside contraction point $\text{p}_{ic}$ and outside contraction point $\text{p}_{oc}$as per following equations:

$$p_{oc} = (1-\gamma)\overline{\text{p}} + \gamma p_r \tag{49}$$
$$p_{ic} = (1-\gamma)\overline{\text{p}} + \gamma \text{p}_{D+1} \tag{50}$$

if $f\ (p_r) < f\ (p_{D+1})$, then calculate the outside contraction point $p_{oc}$ else, calculate the inside contraction point; if $f\ (p_{oc}) \leq f\ (p_r)$, then replace $p_{D+1}$ with $p_{oc}$, and move to Step 6; else, proceed to Step 5; if $f\ (p_{ic}) \leq f\ (p_{D+1})$, then replace $p_{D+1}$ with $p_{ic}$, and move to Step 6 else, proceed to Step 5.

***Step 5:*** Shrink every vertex except $p_i$.

$$V_i = \delta \text{p}_i + (1-\delta)\text{p}_1, \quad \text{where } i = 2, \ldots, D+1 \tag{51}$$

*Step 6:* Stop searching, if end criterion is met. Otherwise begin the subsequent iteration using the updated simplex.

### C. PROPOSED HYBRID INFONM ALGORITHM

This study proposes an algorithm, hybridizing INFO algorithm and nelder mead (NM) method, called as INFONM. These algorithms are adopted due to their different search characteristics to obtain optimal solutions. INFO algorithm is adopted in various optimization problems due to its effective global exploration characteristics. However, in some cases, it traps in local minima due to less exploitation. Its convergence speed is also affected due to local minima trap. On the other hand, NM algorithm is powerful in local exploitation, but it needs initial values of variables to start the search process. NM algorithm is sensitive to initial values of the variables because it traps in local minima if initial points are not appropriate. Therefore, the unique features of these two algorithms are taken into account and a hybridized algorithm, known as INFONM algorithm is proposed in which INFO algorithm is applied at first stage for global exploration and the values obtained from INFO algorithm are utilized as initial points to NM method for local exploitation. The hybrid method is adopted to extract seven unknown parameters of PEMFC and its pseudo code is mentioned as Algorithm 3.

**Algorithm 3** Implementation of Proposed Parameter Extraction Approach

1: **Start Procedure:**
- Set the parameters of INFO Algorithm, Number of search agents = 30, Maximum number of iterations = 1000, Number of runs = 30.
- Set parameters of Nelder-Mead Simplex algorithm $\beta = 2, \alpha = 1, \gamma = \delta = 0.5, Iterations = 1000$.
- Set the lower and upper limits of search ranges from Table 2

2: **Initialization:**
- Initialize INFO Algorithm with random position and evaluate objective function $F_{obj}$ mentioned in Equation (9)
- Initialize Nelder-Mead simplex around the best positions

3: **while** stopping criterion not met **do**
4: Update positions obtained using INFO algorithm.
5: Evaluate fitness of each position using the objective function.
6: Update best positions using INFO algorithm.
7: Apply Nelder-Mead Simplex method to update the simplex around the best position.
8: Calculate fitness of vertices in the simplex method.
9: Update best position.
10: **Return** $F_{obj}$
11: **end while**
12: **End Procedure**

## V. RESULTS AND DISCUSSIONS

In this study, the INFONM algorithm is proposed to extract the unknown parameters of PEMFCs. Four different case studies are considered, using commercially available data sheets from PEMFC stacks such as NedStack PS6, BCS 500-W, Ballard Mark V, and 250 W stack, to evaluate the effectiveness of the INFONM algorithm. The specifications of these PEMFCs are listed in Table 1 and are taken from [16]. The experimental results for these fuel cells are presented as polarization curves in the literature. The necessary experimental data, including voltage and power at different currents, to plot the polarization characteristics have been obtained from [16]. This data is used to validate the results obtained using the proposed INFONM algorithm, with validation based on minimizing the deviation between experimental and estimated polarization characteristics. The lower and upper limits for seven unknown variables are provided in Table 2 and are taken from [16] and [17].

The process of parameter extraction is presented in Fig. 1 in which firstly the data set of experimental current is used in the PEM fuel cell presented in Equation (1)-(8). The unknown parameters are obtained using Algorithm 3 based on objective function mentioned in Equation (9) subject to constraints mentioned in Equation (10) and it produces an output as an estimated voltage corresponding to obtained parameter. Now the sum of squared error is calculated at this step between estimated and experimental voltage. The obtained model is then verified through polarization characteristics I-V and I-P curves. The main aim is to minimize the SSE and obtain closeness between the experimental and estimated polarization characteristics. If this error is not less and model is not verified this process continues till the stopping criteria is met which is number of iterations in this study and parameters are updated at each iteration.

In this study, the results obtained using INFONM for all PEMFC stacks are compared with four well-established algorithms, JAYA algorithm, whale optimization algorithm (WOA), grey wolf optimization (GWO ), bald eagle search algorithm (BES) and also with the algorithms from literature to prove the authenticity of INFONM. The key benefits of this new hybrid approach over other algorithms for the parameter extraction of PEM fuel cell is enhanced accuracy, faster convergence and avoids local minima. The enhanced accuracy for PEMFC parameter extraction can be illustrated from results tabulated in Table 3, 4, 5, and 6 where, INFONM achieves the lower SSE value among all other algorithms in all of the four case studies. Also, Fig. 2 and 3 show the closeness between the estimated polarization characteristics using INFONM and experimental polarization characteristics and clearly demonstrates the accuracy of INFONM in extracting PEMFC unknown parameters. Moreover, due to global exploration and local exploitation of INFONM its fast convergence can be seen from Fig. 4 which shows that within fewer iteration INFONM algorithm converges and avoids local minima whereas, other algorithms in comparison suffer from local minima problem and have relatively slow convergence than INFONM.

The developed PEMFC parameter extraction algorithm based on INFONM, along with other optimization algorithms, is implemented for 30 individual runs. The least value of the objective function among these 30 runs is considered, with each algorithm set to a maximum of 1000 iterations for a fair comparison. Convergence curves and box plot analysis are conducted to demonstrate the speed and robustness of the algorithms. Statistical indices such as the mean, minimum, standard deviation, and maximum value of the objective function are used to assess the robustness and efficiency of the optimization approaches. In this work, SSE is used as the objective function, and INFONM is proposed as a robust approach and compared with other algorithms based on 30 independent runs. The statistical indices are calculated for these 30 runs. The lowest value among the 30 runs is considered as the minimum (best) value, while the highest value is considered as the maximum (worst) value. The minimum SSE value represents the best-case performance, whereas, the maximum SSE value indicates the worst-case performance for the given scenarios. In the proposed work, the INFONM algorithm achieves the lowest SSE values for both best and worst case performances compared to the other algorithms. Additionally, the mean and standard

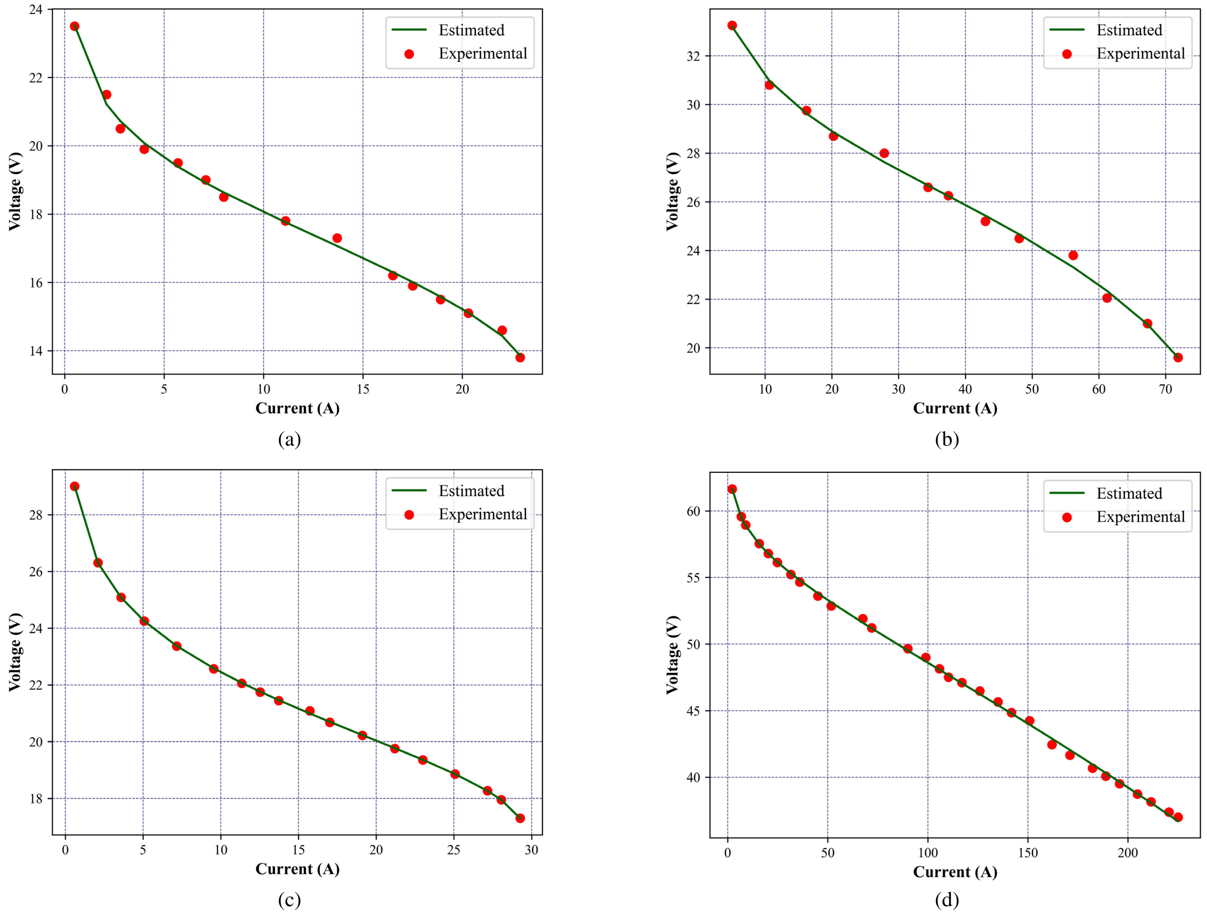



**FIGURE 2.** Experimental and estimated I-V curves using INFONM for (a) 250 W PEMFC stack, (b) Ballard mark V PEMFC stack, (c) BCS 500 W PEMFC stack, and (d) NedStack PS6 PEMFC stack.

deviation of SSE values over the 30 runs are calculated. The mean SSE provides a measure of central tendency and overall accuracy. Comparing the central points of SSE values across algorithms, a lower central point indicates a more superior algorithm. INFONM shows the lowest central point among the algorithms tested, making it a suitable choice for estimating unknown parameters. The standard deviation reflects the spread of SSE values around the mean and indicates variability. A lower standard deviation signifies greater efficiency. INFONM demonstrates the least standard deviation of SSE values among the algorithms, indicating its robustness. Therefore, the statistical analysis in this paper effectively demonstrates the robustness and efficiency of the INFONM method. Additionally statistical analysis is presented as box plot in Fig. 5 and variation of statistical indices for different algorithim is presented in Fig. 6 as a radar chart. Moreover, Wilcoxn and Friedman's tests are performed to test the reliability of the algorithm. Additionally, to provide a significant basis for reliability of INFONM, a percentage of voltage deviation, ($V_{\%v.d}$) is calculated as the percentage of ratio of difference between experimental and estimated voltages to estimated voltage. This analysis is presented in Fig. 7. The performance of INFONM algorithm in extracting the unknown parameters for different case studies is given in the next subsections.

**TABLE 7.** Statistical analysis, Friedman's rank and wilcoxon test for 250 W PEMFC stack.

| STATISTICAL ANALYSIS | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Indices** | **GWO** | **BES** | **JAYA** | **WOA** | **INFO** | **INFONM** |
| **MIN** | 0.332245 | 0.331375 | 0.332421 | 0.331471 | 0.331373 | **0.316798** |
| **Max** | 1.729744 | 2.534844 | 3.89977 | 1.198981 | 0.994037 | **0.351201** |
| **Average** | 0.510792 | 0.564807 | 1.059099 | 0.412171 | 0.391647 | **0.328474** |
| **Standard Deviation** | 0.329452 | 0.512817 | 1.172817 | 0.197554 | 0.141713 | **0.010078** |
| **FRIEDMAN'S RANK AND WILCOXON TEST** | | | | | | |
| **Friedman's rank** | 5 | 6 | 4 | 3 | 2 | 1 |
| **Rank** | 4.582 | 4.566 | 5.895 | 3.687 | 3.223 | 2.112 |
| **R+** | 465 | 465 | 465 | 465 | 465 | |
| **R-** | 0 | 0 | 0 | 0 | 0 | |
| **p-value** | 3.63E-09 | 1.57E-06 | 1.66E-10 | 2.92E-07 | 0.009592 | |
| **Result** | + | + | + | + | + | |

## A. CASE STUDY I: 250 W PEMFC STACK

In this subsection, a commercially available 250 W PEMFC stack is considered to evaluate the performance of the INFONM algorithm in determining the unknown parameters of the fuel cell. The technical parameters of the 250 W PEMFC stack are provided in Table 1.The obtained values of parameters and statistical analysis using different algorithms

**TABLE 8.** Statistical analysis, Friedman's rank and wilcoxon test for Ballard Mark V PEMFC stack.

| STATISTICAL ANALYSIS | | | | | | |
|---|---|---|---|---|---|---|
| **Indices** | **GWO** | **BES** | **JAYA** | **WOA** | **INFO** | **INFONM** |
| **Min** | 0.862466 | 0.912729 | 0.879791 | 0.853608 | 0.853608 | **0.619895** |
| **Max** | 17.68566 | 48.13466 | 12.32251 | 8.106597 | 1.063927 | **0.695214** |
| **Average** | 2.464036 | 7.065664 | 2.176333 | 1.477003 | 0.92313 | **0.647514** |
| **Standard Deviation** | 3.03404 | 11.69074 | 2.56955 | 1.463973 | 0.068084 | **0.027072** |
| **FRIEDMAN'S RANK AND WILCOXON TEST** | | | | | | |
| **Friedman's rank** | 5 | 6 | 4 | 3 | 2 | 1 |
| **Rank** | 4.863 | 4.986 | 5.032 | 4.293 | 2.907 | 1.585 |
| **R+** | 465 | 465 | 465 | 465 | 465 | |
| **R-** | 0 | 0 | 0 | 0 | 0 | |
| **p-value** | 2.26E-11 | 2.26E-11 | 2.26E-11 | 2.26E-11 | 2.26E-11 | |
| **Result** | + | + | + | + | + | |

**TABLE 9.** Statistical analysis, Friedman's rank and wilcoxon test for BCS 500 W PEMFC stack.

| STATISTICAL ANALYSIS | | | | | | |
|---|---|---|---|---|---|---|
| **Indices** | **GWO** | **BES** | **JAYA** | **WOA** | **INFO** | **INFONM** |
| **Min** | 0.014098 | 0.012049 | 0.034567 | 0.012253 | 0.012074 | **0.011100** |
| **Max** | 2.598481 | 4.250028 | 13.13156 | 0.889147 | 0.031639 | **0.013364** |
| **Average** | 0.421495 | 0.872004 | 2.564108 | 0.067141 | 0.018807 | **0.011701** |
| **Standard Deviation** | 0.495492 | 1.229923 | 3.559397 | 0.158403 | 0.006405 | **0.000668** |
| **FRIEDMAN'S RANK AND WILCOXON TEST** | | | | | | |
| **Friedman's rank** | 5 | 6 | 4 | 3 | 2 | 1 |
| **Rank** | 4.863 | 4.986 | 5.032 | 4.293 | 2.907 | 1.585 |
| **R+** | 465 | 465 | 465 | 465 | 465 | |
| **R-** | 0 | 0 | 0 | 0 | 0 | |
| **p-value** | 8.68E-13 | 1.32E-11 | 8.68E-13 | 6.09E-12 | 4.92E-09 | |
| **Result** | + | + | + | + | + | |

**TABLE 10.** Statistical analysis, Friedman's rank and wilcoxon test for Nedstack PS6 PEMFC stack.

| STATISTICAL ANALYSIS | | | | | | |
|---|---|---|---|---|---|---|
| **Indices** | **GWO** | **BES** | **JAYA** | **WOA** | **INFO** | **INFONM** |
| **Min** | 2.371532 | 2.314258 | 2.312285 | 2.303554 | 2.303554 | **1.242416** |
| **Max** | 34.1606 | 39.89727 | 3.115298 | 38.64878 | 2.550982 | **1.34488** |
| **Average** | 8.347803 | 5.736194 | 2.36721 | 5.63253 | 2.36399 | **1.280986** |
| **Standard Deviation** | 6.750463 | 7.742811 | 0.146218 | 7.913846 | 0.080051 | **0.044403** |
| **FRIEDMAN'S RANK AND WILCOXON TEST** | | | | | | |
| **Friedman's rank** | 5 | 6 | 2 | 4 | 3 | 1 |
| **Rank** | 6.146 | 4.983 | 3.345 | 4.786 | 3.489 | 1.351 |
| **R+** | 465 | 465 | 465 | 465 | 465 | |
| **R-** | 0 | 0 | 0 | 0 | 0 | |
| **p-value** | 1.79E-11 | 1.78E-11 | 1.61E-11 | 1.78E-11 | 1.79E-11 | |
| **Result** | + | + | + | + | + | |

are listed in Table 3 and Table 7. The results obtained using INFONM are compared with BES, GWO, WOA, JAYA, INFO and algorithms from literature like HBA, JSA, IAEO, AHA, IAHA, GHO. From Table 3, it is clearly observed that the developed parameter extraction algorithm, INFONM, yields the minimum SSE value of 0.316798 among other algorithms. Statistical analysis performed over 30 runs demonstrates the robustness of the algorithm. From Table 7, it is clearly observed that the developed parameter extraction algorithm, INFONM achieves the lowest values for maximum, minimum, average, and standard deviation of SSE compared to other algorithms. Additionally, INFONM ranks first using Friedman's Rank test and outperforms all other algorithms in every case using the Wilcoxon test, which confirms its reliability in solving the PEMFC parameter extraction problem. A variation of statistical indices for different algorithms is shown in Fig. Fig. 6a which shows that INFONM is a reliable algorithm. The accuracy of the INFONM algorithm is further validated using polarization characteristics, specifically the I-V and I-P curves, as shown in Fig. 2a and Fig. 3a, respectively. The best SSE values obtained among 30 runs is used to plot the polarization curves. The close match between the experimental and estimated polarization curves indicates that INFONM accurately extracted the unknown parameters. Additionally, convergence curve analysis is performed to assess convergence speed, as shown in Fig. 4a. It is observed from Fig. 4a that INFONM converges rapidly as compared to other algorithms. Additionally, the robustness of the INFONM is validated using box-plot analysis as shown in Fig. 5a. It is found that with least value of median and smallest interquartile range INFONM outperform among other algorithms. Further, the voltage deviation percentage is evaluated to check the reliability and it is observed that maximum value of $V_{\%v.d}$ is 1.688% as shown in Fig. 7a.

### B. CASE STUDY II: BALLARD MARK V PEMFC STACK

This case study evaluates the performance of INFONM on a commercially available Ballard Mark V fuel cell stack. The technical specifications of Ballard Mark V are listed in Table 1. The results obtained using INFONM are compared with GWO, BES, JAYA, WOA, and INFO. Moreover, comparison with algorithms from literature like, GOA, PFA, NNO, AHA, and GHO are considered.The objective function values along with obtained parameters using different algorithms are given in Table 4 where as, statistical analysis based on objective function values is presented in Table 8. From Table 4, it can be observed that INFONM produced a minimum value of SSE of 0.619895 over other algorithms. The statistical analysis over 30 runs, tabulated in Table 8 shows a least value of maximum, minimum, average and standard deviation of SSE and obtained first rank in solving PEMFC parameter extraction problem. The variations of statistical indices shown in Fig. 6b indicate that INFONM is a robust algorithm. Moreover, the accuracy of the proposed algorithm can be observed by a good closeness between the experimental and estimated I-V and I-P characteristics as mentioned in Fig. 2b and Fig. 3b, respectively. Furthermore, from Fig. 5b convergence curves for different algorithm is shown for this case study and it is observed that INFONM effectively converges faster than other algorithm. Box plot analysis is shown in Fig. 4b which further validates the robustness of the algorithm by showing least median and smaller interquartile range among other algorithms. The maximum value of $V_{\%v.d}$ is obtained as 2.69% for this case study and is presented as shown in Fig. 7b. Thus, the reliability of INFONM in extracting unknown PEMFC parameters for this case study is concluded from the above discussions.

### C. CASE STUDY III: BCS 500 W

In this subsection, INFONM algorithm along with JAYA, GWO, BES, WOA and INFO algorithms have been implemented for BCS 500 W. The results have also been compared

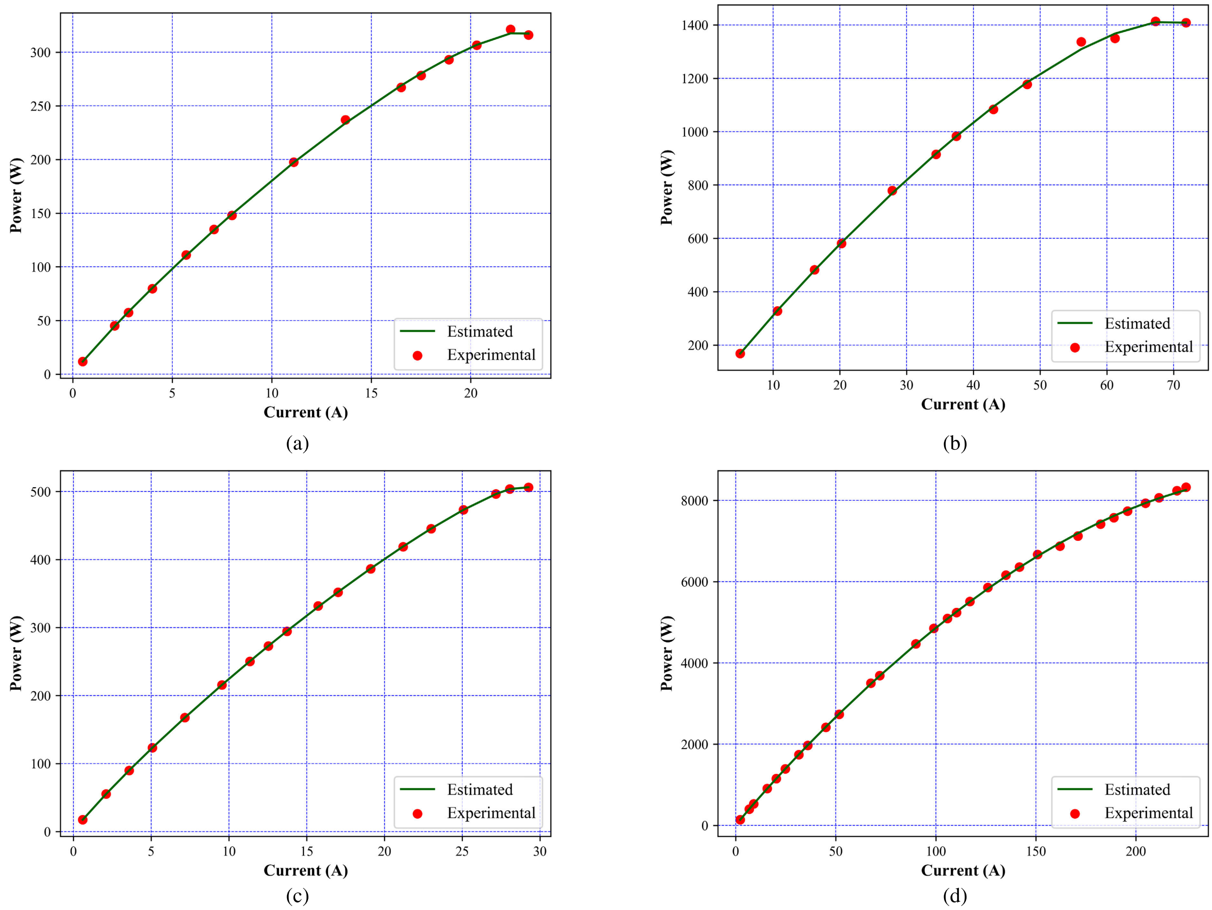



**FIGURE 3. Experimental and estimated I-P curves using INFONM for (a) 250 W PEMFC stack, (b) Ballard mark V PEMFC stack, (c) BCS 500 W PEMFC stack, and (d) NedStack PS6 PEMFC stack.**

with algorithms implemented in literature like SSO, HBA, FOA, ICA, JSA, and AHA to illustrate the authenticity of developed algorithm. The technical specifications used for this study are tabulated in Table 1. Results using different algorithms and the values of obtained parameters are mentioned in 5 which elucidates that INFONM shows a minimum SSE of 0.01110012 over all other algorithms. 2c and 3c presents the polarization characteristics of BCS 500 W and it is observed that there is a close approximation of experimental and estimated I-V and I-P characteristics, respectively which further demonstrates the accuracy of INFONM in identifying optimal values of unknown parameters. The statistical analysis is also tabulated in Table 9, and it reveals that INFONM with least value of average, standard deviation, minimum and maximum for SSE outperformed over all other algorithms. Further, it is observed from Fig. 6c that INFONM performed better in terms of variations of statistical indices over different algorithms. Fig. 4c shows the convergence characteristics using different algorithm for BCS 500 W and it is concluded that INFONM delivers faster convergence over other algorithms. The robustness of INFONM for BCS 500 W fuel cell stack is validated using box plot as shown in Fig. 5c. It is observed that INFONM with least median and small interquartile range outperformed among other algorithms. Furthermore, a highest $V_{\%v.d}$ of 0.458%, as shown in Fig. 7c, illustrates the reliability of INFONM to solve the PEMFC parameter extraction problem effectively.

### *D. CASE STUDY IV: NEDSTACK PS6 PEMFC STACK*

In this case study, the NedStack PS6 fuel cell is considered, and the performance of the INFONM algorithm is examined in comparison with GWO, BES, JAYA, WOA, and INFO algorithms. The results are also compared with algorithms from the literature, such as GSA, VSA, GA, SSA, and MRFO. The technical specifications of NedStack PS6 fuel cell are listed in Table 1. The value of unknown parameters along with objective function evaluations for different algorithm is tabulated in in Table 6. From this table it can be observed that INFONM identifies the unknown parameters effectively with least SSE value of 1.2424162. Fig. 2d and Fig. 3d demonstrate a close match between the experimental and estimated I-V and I-P characteristics, respectively, further illustrating the accuracy of INFONM in extracting unknown parameters. The superiority of INFONM is further confirmed by statistical analysis, as presented in Table 10. This table

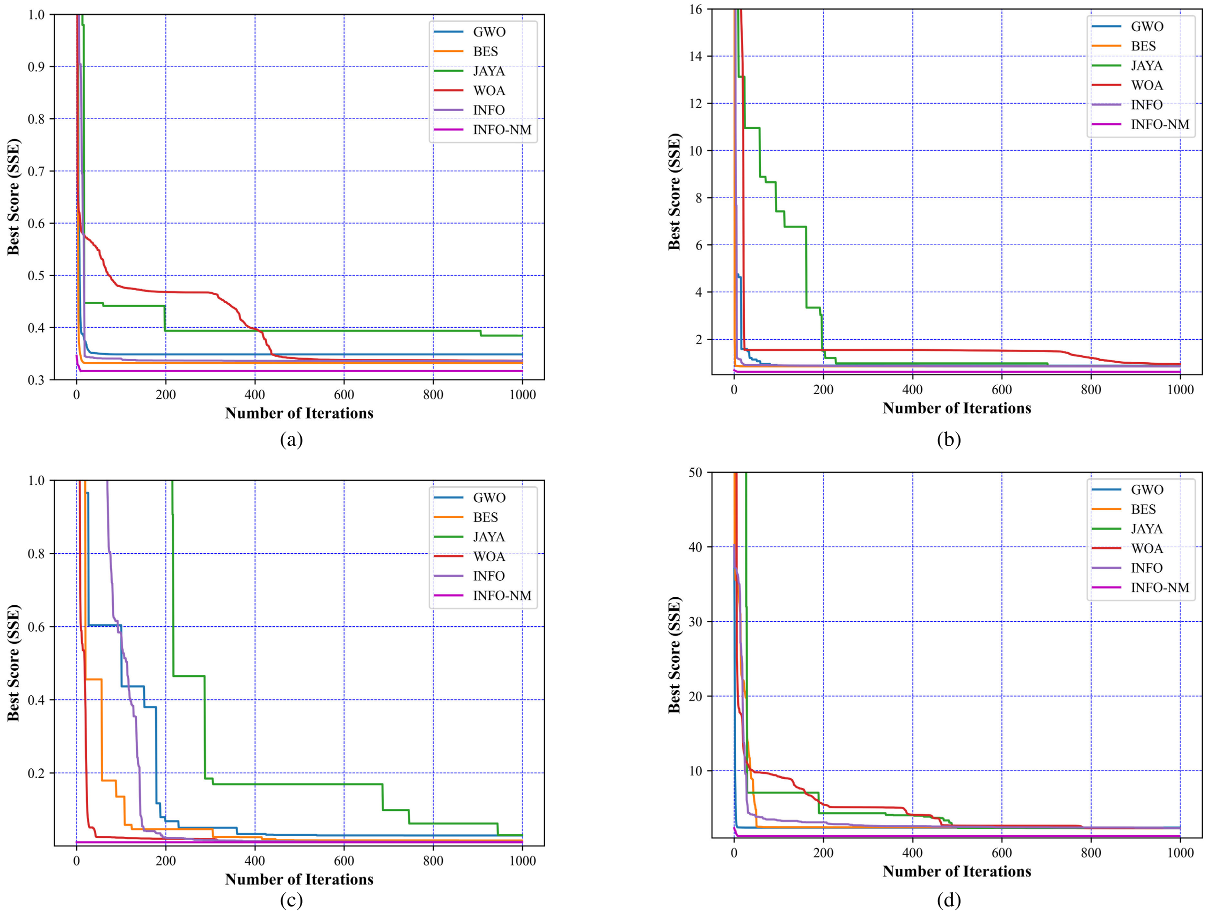



**FIGURE 4.** Convergence curves for (a) 250 W PEMFC stack, (b) Ballard mark V PEMFC stack, (c) BCS 500 W PEMFC stack, and (d) NedStack PS6 PEMFC stack.

shows that INFONM achieves the lowest average, standard deviation, maximum, and minimum values of SSE over 30 runs. Additionally, INFONM ranks first using Friedman's rank test and outperforms all other algorithms in solving the parameter extraction problem. The variations of statistical indices for all algorithms is as shown in Fig. 6d and reveal the effectiveness of INFONM over other algorithms. Box plot analysis is further presented as shown in Fig. 5d which shows a small interquartile range and least value of median over all other algorithms. The reliability of INFONM is also observed from Fig. 7d, with a highest $V_{\%v,d}$ of 1.242%. Furthermore, from convergence curve, as shown in Fig. 4d, it can be observed that the developed algorithm demonstrates faster convergence speed compared to other algorithms, effectively solving parameter extraction problems.

## VI. SENSITIVITY ANALYSIS

A Global Sensitivity Study (GSS) is conducted to analyze how variations in the extracted parameters of a PEM fuel cell impact the sum of squared error calculations. This method is useful for understanding the relationship between the extracted parameters and the performance of the model. Sensitivity analysis using Sobol indicators provides insights into the first-order effects $S_i$ and overall effects $S_o$ of unknown parameters on a fuel cell model output. The first-order effect $S_i$ reflects the influence of individual parameters on the model's output, indicating that a higher $S_i$ value means a greater impact of that parameter on the output when considered alone. In contrast, the overall effect $S_o$ captures the total impact of each parameter, including both its direct effect and interactions with other parameters. A higher $S_o$ value suggests that the parameter, along with its interactions, has a more significant influence on the model output. This sensitivity analysis, based on $S_i$ and $S_o$ indicators, helps identify crucial parameters whose small variations can significantly affect the fuel cell model's performance. It also aids in uncertainty analysis by determining which parameters are highly sensitive to small changes. Sobol sensitivity indicators, such as $S_i$ for first-order effects and $S_o$ for overall effects, are determined through extensive Monte Carlo simulations. $S_i$ shows the individual effect of parameter variations on the model output, while $S_o$ provides a comprehensive view by accounting for parameter interactions. The discrepancies between $S_i$ and $S_o$ reveal the extent of parameter interactions. When interactions are absent, $S_i$ and $S_o$ are equal and if $S_i$ is of higher values,

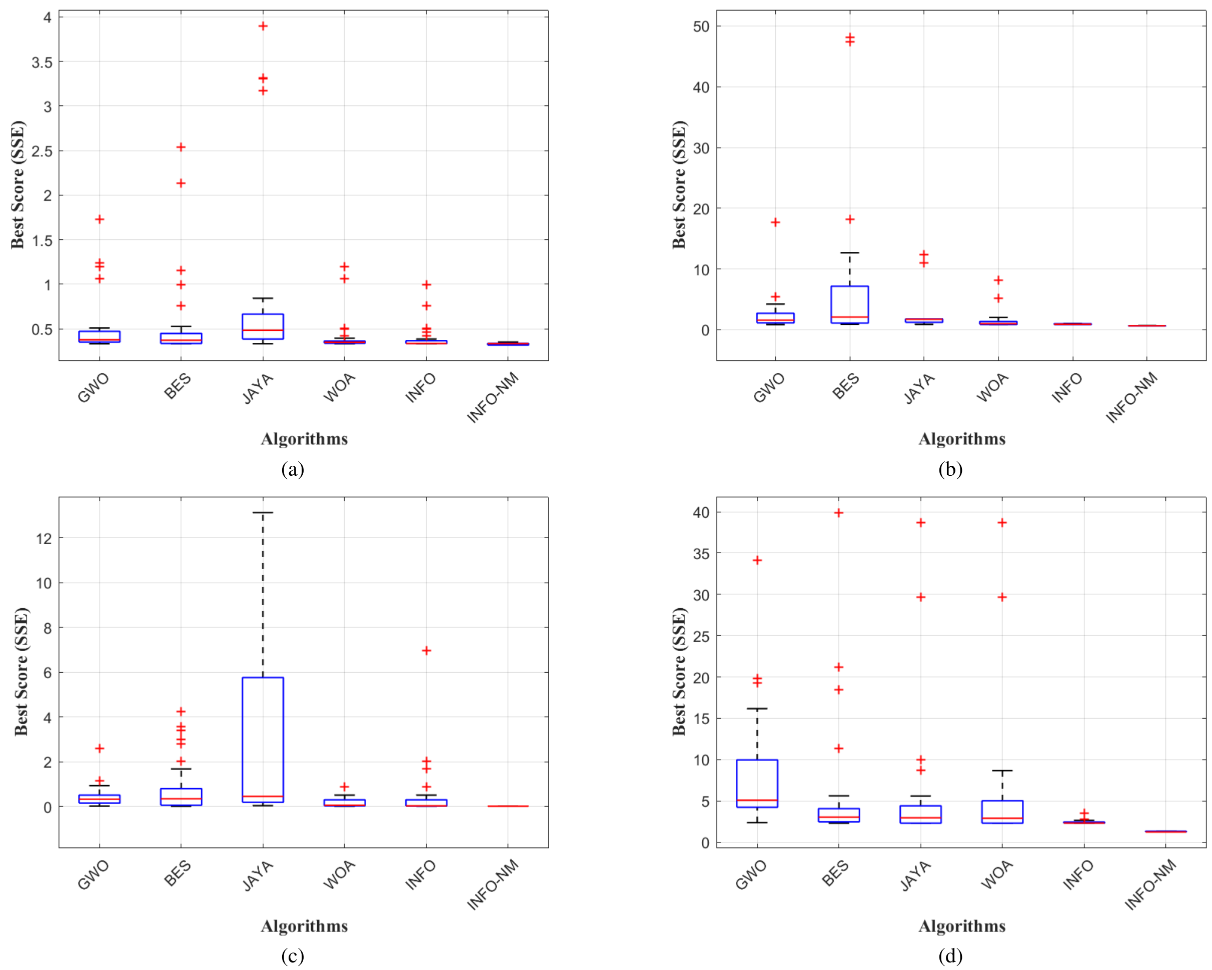



**FIGURE 5.** Box plot for (a) 250 W PEMFC stack, (b) Ballard mark V PEMFC stack, (c) BCS 500 W PEMFC stack, and (d) NedStack PS6 PEMFC stack.

it shows a greater parameter importance. In this study, the range of parameter variations is set at $\pm 10\%$ of the optimized values for different PEMFC stacks and the number of samples are set at 20,000. The resulting values of the Sobol sensitivity indicators for each optimized parameter for all of the four case studies are summarized in Table 11. The analysis highlights that PEMFC fuel cell model is substantially dependent on two key parameters, $\xi_2$ and $b$, which is evidenced by their notably high $S_i$ and $S_o$ values. Parameters, $\xi_1, \xi_3, \xi_4$ exhibit moderate sensitivity, while $\lambda$ and $R_C$ show minimal sensitivity. These findings reveal the highly nonlinear nature of the mathematical model of PEM fuel cell and highlights that even a small variation in the optimized parameters can significantly impact the output performance, particularly concerning $\xi_2$ and $b$.

## VII. ROBUSTNESS OF INFONM FOR DIFFERENT PEMFC STACK UNDER DIFFERENT SCENARIOS

### A. 250 W PEMFC STACK

In this subsection, firstly INFONM is applied to map the experimental polarization characteristics at different operating temperatures and pressures. The 250 W PEMFC stack is considered at different operating conditions. The technical specifications are tabulated in Table 1 where as, temperature, inlet hydrogen pressure and outlet oxygen pressure are set at different values for four different scenarios. These scenarios are set at four different reactants pressure ($H_2/O_2$) of 3/5, 1.5/1.5, 1/1 and 2.5/3 bar respectively where as, for first scenario temperature is set at 353.15 K and for other three scenarios temperature is set at 343.15. From Fig. 8, it is observed that the estimated I-V characteristics using INFONM accurately map with experimental I-V characteristics which further demonstrates the effectiveness of INFONM to perform better even at different operating conditions.

### B. PERFORMANCE OF 250 W AND BCS 500 W AT DIFFERENT TEMPERATURES AND PRESSURES

To analyze the effect of temperature and pressure variations on the polarization characteristics and verify the model's authenticity, two PEMFC stacks, namely BCS 500 W and 250 W, are considered. The technical specifications of these stacks remain the same as those listed in Table 1, except for changes in temperature and reactant pressures

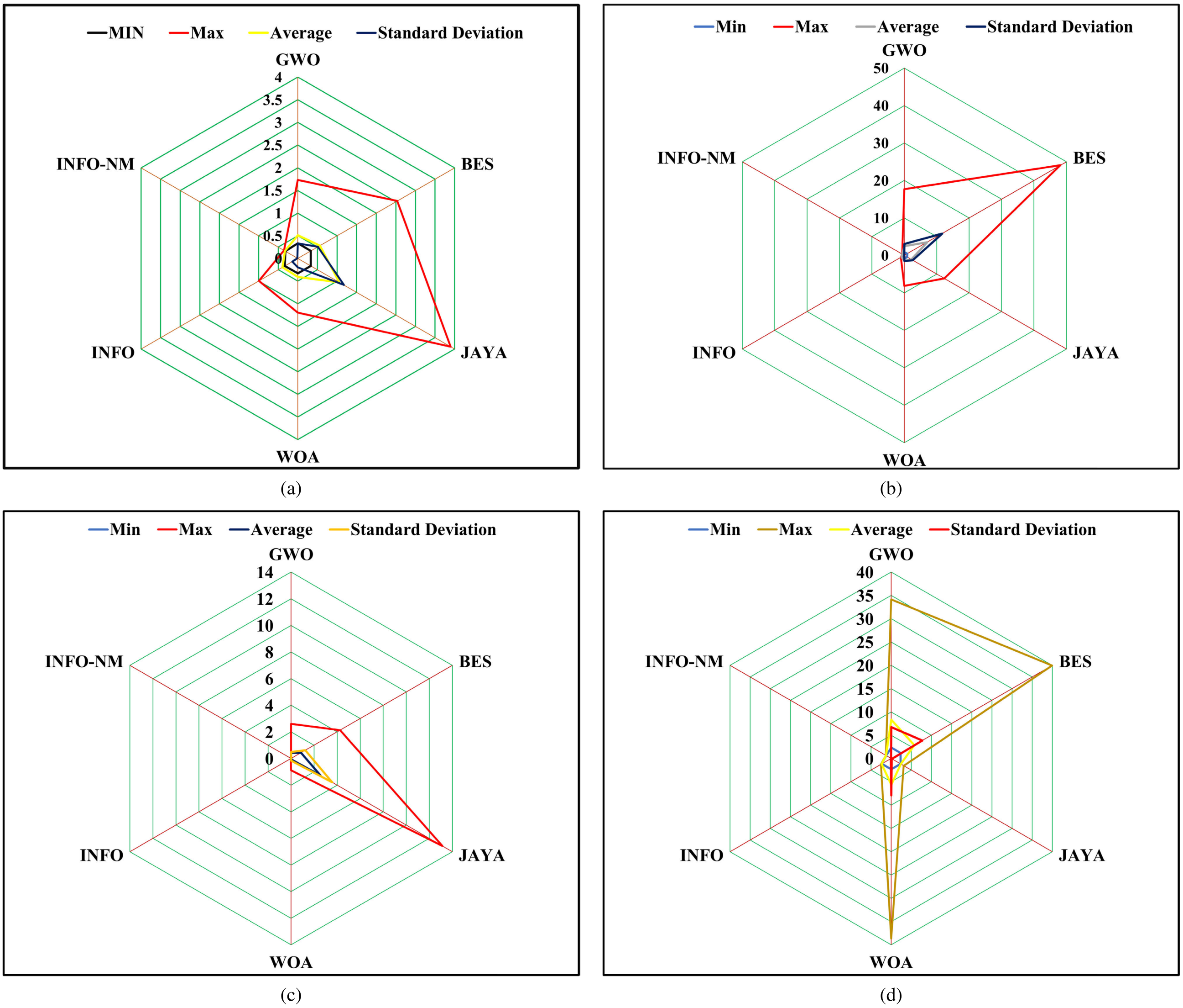



**FIGURE 6.** Variation of statistical indices for (a) 250 W PEMFC stack, (b) Ballard Mark V PEMFC stack, (c) BCS 500 W PEMFC stack, and (d) NedStack PS6 PEMFC stack.

**TABLE 11.** Sobol sensitivity indicators for extracted PEMFC parameters.

| | $\xi_1(V)$ | $\xi_2(V/K)$ | $\xi_3(V/K)$ | $\xi_4(V/K)$ | $\lambda$ | $b(V)$ | $R_c$ ($\Omega$) |
|---|---|---|---|---|---|---|---|
| **250 W** | | | | | | | |
| $S_i$ | 0.0267 | 0.5306 | 0.0181 | 0.0058 | 5.96E-05 | 0.2429 | 7.19E-04 |
| $S_o$ | 0.072 | 0.6908 | 0.0534 | 0.0111 | 8.44E-04 | 0.3456 | 5.77E-05 |
| **BCS 500 W** | | | | | | | |
| $S_i$ | 0.0295 | 0.5509 | 0.0248 | 0.0071 | 5.27E-04 | 0.1918 | -2.25E-04 |
| $S_o$ | 0.0825 | 0.7315 | 0.0703 | 0.0149 | 4.95E-04 | 0.2988 | 1.19E-04 |
| **Ballard Mark V** | | | | | | | |
| $S_i$ | 0.038 | 0.6626 | 0.0277 | 0.0136 | 4.90E-03 | 0.1407 | 1.20E-03 |
| $S_o$ | 0.0686 | 0.7652 | 0.0508 | 0.0243 | 7.70E-03 | 0.195 | 5.75E-04 |
| **NedStack PS6** | | | | | | | |
| $S_i$ | 0.0339 | 0.7445 | 0.0245 | 0.0186 | 2.80E-04 | 0.0027 | 2.00E-03 |
| $S_o$ | 0.1131 | 0.913 | 0.08903 | 0.0569 | 2.00E-03 | 0.0023 | 6.10E-03 |

under different scenarios. Initially, an analysis is conducted at different temperatures, where the reactant pressures are set as specified in Table 1 for both stacks. The temperature is varied from 303 K to 353 K for the 250 W PEMFC stack and from 303 K to 333 K for the BCS 500 W PEMFC stack. From Fig.9, it is observed that with increase

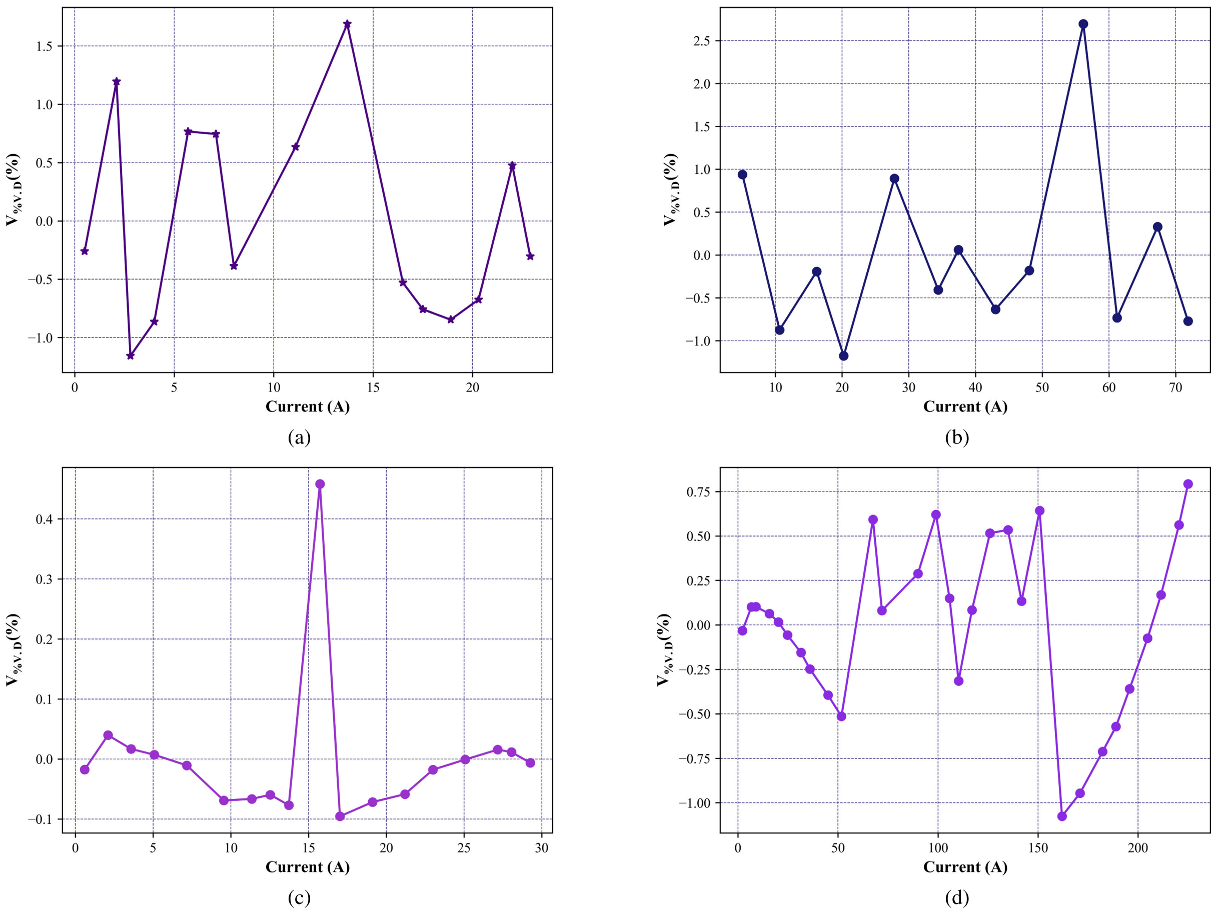



**FIGURE 7.** Percentage voltage deviation for different PEMFC stacks (a) 250 W PEMFC stack, (b) Ballard mark V PEMFC stack, (c) BCS 500 W PEMFC stack, and (d) NedStack PS6 PEMFC stack.

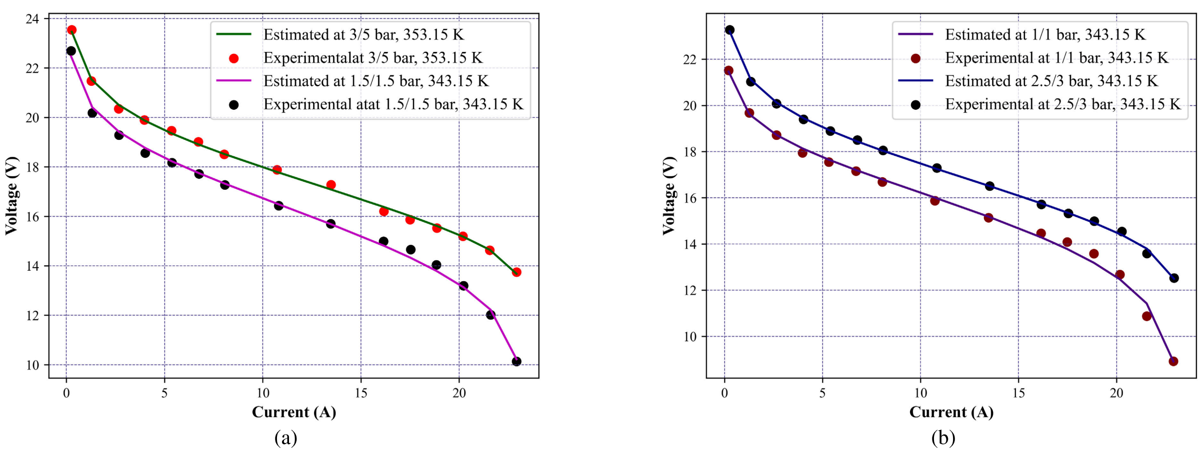



**FIGURE 8.** Estimated and experimental I-V curves at different temperatures and pressures for 250 W PEMFC stack.

in temperature, the voltage and power output of 250 W PEMFC stack increase. This relationship can be verified from Equation (2), (3), (4) and (7). From Equation (2) it is observed that there is a linear relationship between temperature and the nernst voltage and, therefore, there is increase in total voltage but at the same time, it is observed that the total voltage decreases due to rise in potential drops due to increase in temperature as per Equation (3), (4) and (7). However, the rise in potential drops are less significant than that of in the nernst voltage. Therefore, the total voltage

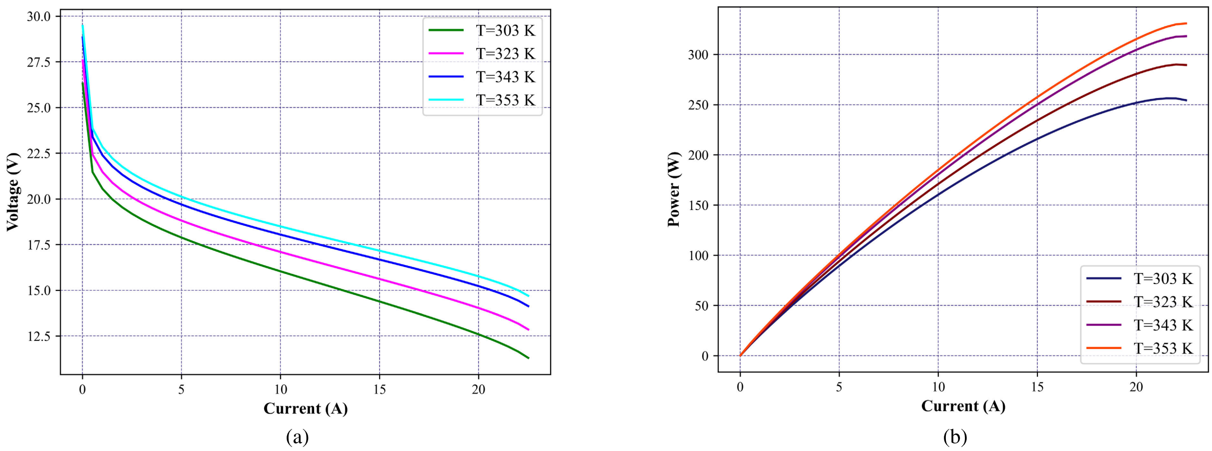



**FIGURE 9.** Polarization characteristics of 250 W PEMFC stack at different temperatures.

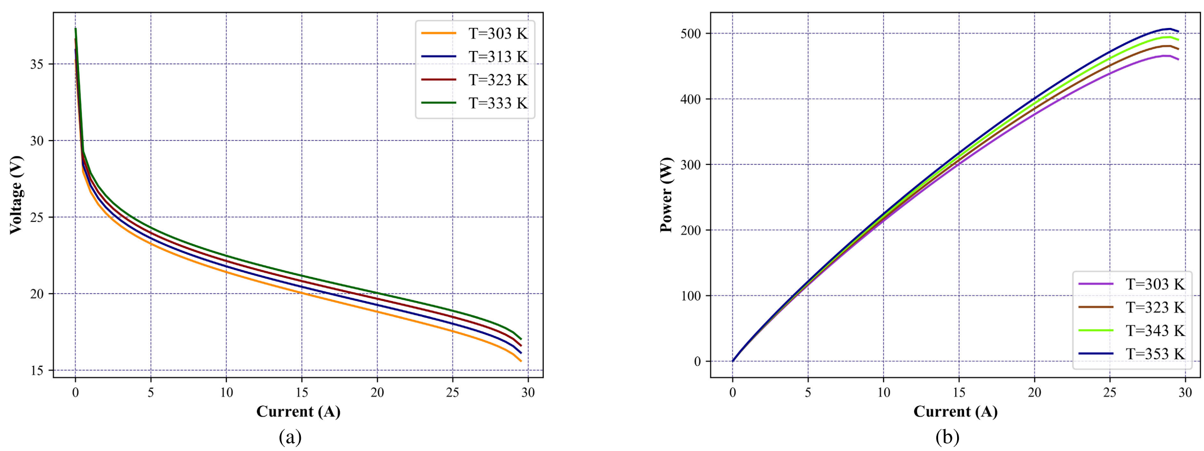



**FIGURE 10.** Polarization characteristics of BCS 500 W PEMFC stack at different temperatures.

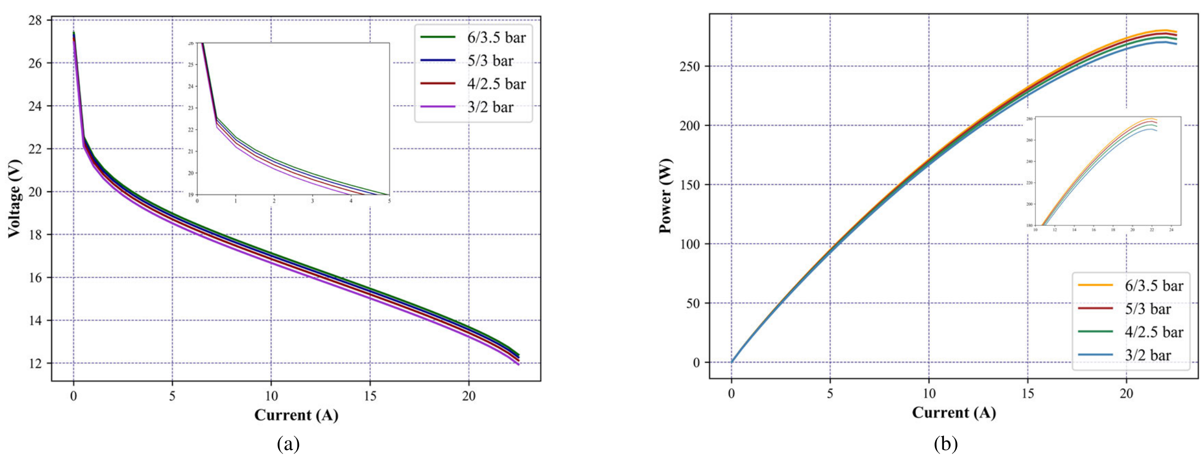
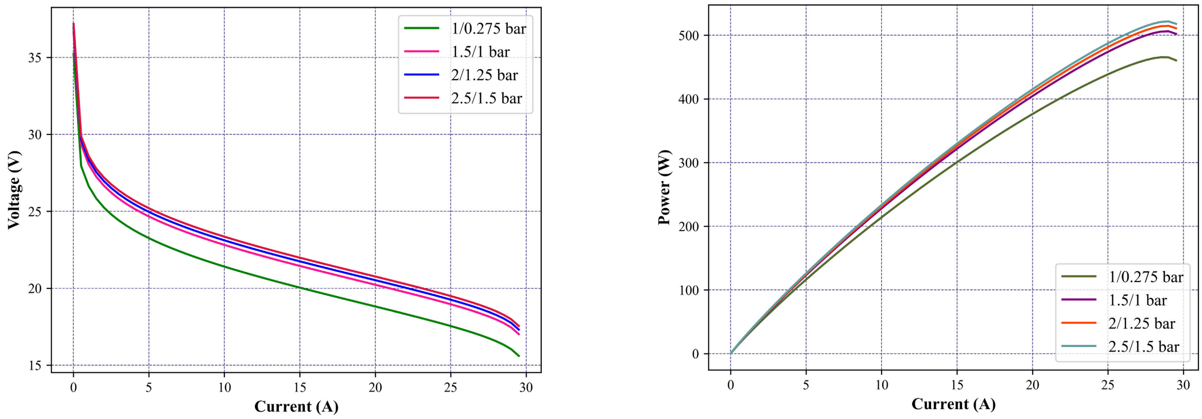



**FIGURE 11.** Polarization characteristics of 250 W stack at different pressures.

increases with rise in temperature and the same results are obtained for power with temperature rise of PEMFC as power is the product of voltage and current. The same can be observed from Fig. 10 for BCS 500 W PEMFC stack that with rise in temperature, the total output voltage of BCS 500 W PEMFC stack increases and thus, validates




(a) (b)

**FIGURE 12.** **Polarization characteristics of BCS 500 W PEMFC stack at different pressures.**

**TABLE 12.** **Estimated and experimental voltages at different pressures and temperature for 250 W PEMFC stack.**

| 3/5 bar and 353.15 K | | | 1.5/1.5 bar 343.15 K | | | 1/1 bar and 343.15 K | | | 2.5/3 bar and 343.15 K | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| $I_{fc}$ (A) | $V_{exp.}$ (V) | $V_{est.}$ (V) | $I_{fc}$ (A) | $V_{exp.}$ (V) | $V_{est.}$ (V) | $I_{fc}$ (A) | $V_{exp.}$ (V) | $V_{est.}$ (V) | $I_{fc}$ (A) | $V_{exp.}$ (V) | $V_{est.}$ (V) |
| 0.2729 | 23.541 | 23.46680 | 0.24170 | 22.6916 | 22.4663322 | 0.20460 | 21.5139 | 21.46384 | 0.2582 | 23.271 | 23.20604 |
| 1.2740 | 21.4756 | 21.53854 | 1.31770 | 20.1869 | 20.4107225 | 1.26190 | 19.6737 | 19.61494 | 1.3340 | 21.028 | 21.11572 |
| 2.6603 | 20.3484 | 20.50985 | 2.68190 | 19.2897 | 19.4161499 | 2.64330 | 18.7154 | 18.72179 | 2.6471 | 20.0748 | 20.12983 |
| 3.9734 | 19.8969 | 19.87913 | 4.01180 | 18.5607 | 18.7652952 | 3.97340 | 17.9449 | 18.13786 | 4.0281 | 19.4019 | 19.44534 |
| 5.3547 | 19.4642 | 19.35527 | 5.37550 | 18.1682 | 18.2248434 | 5.32060 | 17.5497 | 17.6501 | 5.3919 | 18.8972 | 18.90943 |
| 6.7190 | 19.0127 | 18.91090 | 6.75630 | 17.7196 | 17.7440138 | 6.70190 | 17.1545 | 17.20309 | 6.7726 | 18.5047 | 18.43976 |
| 8.0321 | 18.5049 | 18.52326 | 8.06890 | 17.2710 | 17.3214315 | 8.04910 | 16.6843 | 16.79406 | 8.0852 | 18.0561 | 18.03290 |
| 10.7265 | 17.8835 | 17.79347 | 10.8134 | 16.4299 | 16.4869205 | 10.7265 | 15.8752 | 16.00893 | 10.829 | 17.2897 | 17.24726 |
| 13.4720 | 17.2808 | 17.08530 | 13.4556 | 15.7009 | 15.6883856 | 13.4720 | 15.1411 | 15.18365 | 13.523 | 16.5047 | 16.50598 |
| 16.1664 | 16.2089 | 16.38005 | 16.1488 | 14.9907 | 14.8180476 | 16.1494 | 14.4634 | 14.29154 | 16.165 | 15.7196 | 15.75951 |
| 17.4966 | 15.8701 | 16.01403 | 17.5295 | 14.6542 | 14.3222315 | 17.4795 | 14.087 | 13.78449 | 17.545 | 15.3271 | 15.34372 |
| 18.8608 | 15.5312 | 15.61441 | 18.8423 | 14.0374 | 13.7935554 | 18.8438 | 13.5792 | 13.18577 | 18.858 | 14.9907 | 14.91655 |
| 20.1910 | 15.1923 | 15.18320 | 20.2234 | 13.1963 | 13.1299423 | 20.1739 | 12.6772 | 12.46743 | 20.273 | 14.5421 | 14.39262 |
| 21.5553 | 14.6282 | 14.64881 | 21.6049 | 12.0187 | 12.2177706 | 21.5382 | 10.8743 | 11.42467 | 21.552 | 13.5888 | 13.79408 |
| 22.9195 | 13.745 | 13.67763 | 22.9189 | 10.1308 | 10.2245764 | 22.9025 | 8.9213 | 8.912803 | 22.933 | 12.5234 | 12.49099 |

the accuracy of PEMFC model. For analysis of variation of reactant pressures, the temperature for both PEMFC stacks is considered as mentioned in Table 1. The reactants' pressures for 250 W PEMFC stack are set at 6/3.5, 5/3, 4/2, and 3/2 bar and for BCS 500 W they are set at 1/0.2075, 1.5/1, 2/1.25, and 2.5/1.5 bar. From Fig. 11 and Fig. 12, it is observed that, with rise in the inlet pressure of reactants, both output voltage and power improve. This relationship can be verified through Equation (2), which indicates that the Nernst voltage is logarithmically proportional to the reactants' pressure. As a result, an increase in reactant pressure leads to a rise in Nernst voltage. However, due to the logarithmic nature of the relationship, this increase is relatively small. Consequently, the slight increase in Nernst voltage results in a modest rise in the total output voltage of the PEMFC stack. This observation directly correlates the performance of the 250 W and BCS 500 W stacks with the proposed accurate PEMFC model using the INFONM algorithm, verifying that INFONM is a robust algorithm for accurately extracting unknown parameters. From the discussions in case studies I-V, it is concluded that the INFONM algorithm effectively estimates the values of the unknown PEMFC parameters. Among other algorithms, INFONM stands out in terms of accuracy, convergence speed, and reliability. Additionally, INFONM is capable of estimating unknown parameters under dynamic conditions, including varying temperatures and pressures. It accurately determines the polarization characteristics and aligns them with experimental results under these conditions, demonstrating its reliability. The robustness of the INFONM algorithm across different

**TABLE 13. Estimated and experimental voltages for NeDStack PS6, BCS500 W, 250 W and ballarad mark V PEMFC stack.**

| Nedstack Ps6 | | | BCS 500 W | | | 250 W | | | Ballard Mark V | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| $I_{fc}$ (A) | $V_{exp.}$ (V) | $V_{est.}$ (V) | $I_{fc}$ (A) | $V_{exp.}$ (V) | $V_{est.}$ (V) | I_fc (A) | $V_{exp.}$ (V) | $V_{est.}$ (V) | $I_{fc}$ (A) | $V_{exp.}$ (V) | $V_{est.}$ (V) |
| 2.25 | 61.64 | 61.65961 | 0.60 | 29.00 | 29.00510 | 0.5 | 23.5 | 23.52378 | 5.060 | 33.25 | 33.19049 |
| 6.75 | 59.57 | 59.50987 | 2.10 | 26.31 | 26.29956 | 2.1 | 21.5 | 21.21665 | 10.626 | 30.80 | 30.97584 |
| 9.00 | 58.94 | 58.87997 | 3.58 | 25.09 | 25.08579 | 2.8 | 20.5 | 20.7229 | 16.192 | 29.75 | 29.62764 |
| 15.75 | 57.54 | 57.50385 | 5.08 | 24.25 | 24.24831 | 4.0 | 19.9 | 20.07935 | 20.240 | 28.70 | 28.85761 |
| 20.25 | 56.80 | 56.79099 | 7.17 | 23.37 | 23.37249 | 5.7 | 19.5 | 19.38561 | 27.830 | 28.00 | 27.63304 |
| 24.75 | 56.13 | 56.16206 | 9.55 | 22.57 | 22.58559 | 7.1 | 19.0 | 18.9120 | 34.408 | 26.60 | 26.67289 |
| 31.50 | 55.23 | 55.31612 | 11.35 | 22.06 | 22.07466 | 8 | 18.5 | 18.63449 | 37.444 | 26.25 | 26.23802 |
| 36.00 | 54.66 | 54.79553 | 12.54 | 21.75 | 21.76294 | 11.1 | 17.8 | 17.76251 | 43.010 | 25.20 | 25.43023 |
| 45.00 | 53.61 | 53.82176 | 13.73 | 21.45 | 21.46652 | 13.7 | 17.3 | 17.06706 | 48.070 | 24.50 | 24.66275 |
| 51.75 | 52.86 | 53.13184 | 15.73 | 21.09 | 20.99337 | 16.5 | 16.2 | 16.29809 | 56.166 | 23.80 | 23.30977 |
| 67.50 | 51.91 | 51.60229 | 17.02 | 20.68 | 20.69974 | 17.5 | 15.9 | 16.00875 | 61.226 | 22.05 | 22.34000 |
| 72.00 | 51.22 | 51.17870 | 19.11 | 20.22 | 20.23451 | 18.9 | 15.5 | 15.58162 | 67.298 | 21.00 | 20.96015 |
| 90.00 | 49.66 | 49.51655 | 21.20 | 19.76 | 19.77157 | 20.3 | 15.1 | 15.11499 | 71.852 | 19.60 | 19.60156 |
| 99.00 | 49.00 | 48.69623 | 23.00 | 19.36 | 19.36345 | 22.0 | 14.6 | 14.43347 | | | |
| 105.80 | 48.15 | 48.07821 | 25.08 | 18.86 | 18.86018 | 22.9 | 13.8 | 13.85875 | | | |
| 110.30 | 47.52 | 47.66943 | 27.17 | 18.27 | 18.26715 | | | | | | |
| 117.00 | 47.1 | 47.06039 | 28.06 | 17.95 | 17.94796 | | | | | | |
| 126.00 | 46.48 | 46.24023 | 29.26 | 17.30 | 17.30111 | | | | | | |
| 135.00 | 45.66 | 45.41616 | | | | | | | | | |
| 141.80 | 44.85 | 44.79004 | | | | | | | | | |
| 150.80 | 44.24 | 43.95569 | | | | | | | | | |
| 162.00 | 42.45 | 42.90681 | | | | | | | | | |
| 171.00 | 41.66 | 42.05420 | | | | | | | | | |
| 182.30 | 40.68 | 40.96989 | | | | | | | | | |
| 189.00 | 40.09 | 40.31908 | | | | | | | | | |
| 195.80 | 39.51 | 39.65213 | | | | | | | | | |
| 204.80 | 38.73 | 38.75888 | | | | | | | | | |
| 211.50 | 38.15 | 38.08572 | | | | | | | | | |
| 220.50 | 37.38 | 37.16993 | | | | | | | | | |
| 225.00 | 37.00 | 36.70687 | | | | | | | | | |

scenarios further illustrates that accurate polarization characteristics at various temperatures and pressures can be obtained using the extracted parameters, matching closely with the outcomes of the PEMFC mathematical model. Moreover, INFONM is easy to implement. While the Nelder-Mead algorithm requires several parameters, there is no need for tuning them, as standard values produce satisfactory results, as shown in this study. Therefore, a straightforward approach has been applied to solve the nonlinear, multivariate, and complex optimization problem of PEMFC parameter extraction. INFONM is thus highly recommended for PEMFC model parameter extraction. However, it is important to note that the above discussions are limited to the application of INFONM to the PEMFC parameter extraction problem. Additionally, according to the no free lunch theorem, there is no single algorithm that performs well on every problem. For this reason, INFONM and five other algorithms were also tested in this study. The results showed that INFONM outperformed the others, proving its competitiveness in solving this problem. It should be further considered that these algorithms were tested only for PEMFC parameter extraction, they should also be evaluated on other complex optimization tasks to investigate their broader competitiveness.

## VIII. CONCLUSION

A new efficient and robust hybrid INFONM technique is proposed to extract the optimal parameters of PEMFC model. Four different PEMFC stacks viz NedStack PS6, BCS 500 W, Ballard Mark V and 250 W Stack are considered to evaluate the effectiveness of hybrid approach in extracting the unknown parameters of the mentioned fuel cell stacks and obtaining the accurate polarization characteristics that matches with the experimental polarization characteristics. This approach is helpful in obtaining accurate mathematical model and can be helpful in the optimized operation of PEMFC in various applications such as fuel cell integration with renewable energy sources, energy management, energy storage systems, microgrids etc. Also, this model helps in monitoring the performance and ensuring the efficient control and use of the PEMFC. Seven unknown parameters ($\xi_1, \xi_2, \xi_3, \xi_4, \lambda, b$, and $R_C$) have been evaluated optimally using INFONM based on sum of squared error as the objective function. The closeness between the experimental and estimated polarization characteristics, I-V and I-P curves validated the accuracy of the proposed approach. It is found that INFONM accurately determines the values of seven unknown parameters and is a good identifier that closely matches with the experimental polarization characteristics. Moreover, a fair comparison between the results obtained using INFONM algorithm and recent optimization approaches as well as algorithms from the literature is performed to confirm its superiority. The Friedman and Wilcoxon test assessed the statistical validity and demonstrated that the INFONM outperformed among other algorithms and obtained the first rank in all case studies. Moreover, convergence curves and box plot analysis demonstrate that INFONM converges rapidly and proves its robustness with least median and small interquartile range in box plot. The sensitivity analysis considering SOBOL indicators demonstrates that any small variation in extracted parameter can greatly influence the PEMFC model. Therefore, the INFONM algorithm is proven to be an effective and robust approach in identifying PEMFC model unknown parameters. It should be further considered that INFONM algorithm is tested only for PEMFC parameter extraction, it should also be evaluated on other complex optimization tasks to investigate their broader competitiveness. Further, the future studies will involve the performance analysis and comparison of INFONM with other standard algorithms such as phasor particle swarm optimization etc. Moreover, the future work in this research will be related to integrating the derived accurate PEMFC model into energy systems and investigate its performance under real scenarios.

## APPENDICES

The authors have provided the measured value of volatges and currents at different temperatures and pressure for the 250 W PEMFC STACK in Table 12 for more clarification and validation of the results. Also, the measured value of volatges and currents for NedStack PS6, BCS 500 W, 250 W and Ballard Mark V have been presented in Table 13.

## REFERENCES


[1] A. S. Menesy, H. M. Sultan, A. Selim, M. G. Ashmawy, and S. Kamel, ‘‘Developing and applying chaotic Harris Hawks optimization technique for extracting parameters of several proton exchange membrane fuel cell stacks,’’ *IEEE Access*, vol. 8, pp. 1146–1159, 2020.

[2] A. A. Z. Diab, M. A. Tolba, A. G. A. El-Magd, M. M. Zaky, and A. M. El-Rifaie, ‘‘Fuel cell parameters estimation via marine predators and political optimizers,’’ *IEEE Access*, vol. 8, pp. 166998–167018, 2020.

[3] R. Khajuria, S. Yelisetti, R. Lamba, and R. Kumar, ‘‘Optimal model parameter identification of solid oxide fuel cell using honey badger algorithm,’’ in *Proc. Int. Conf. Comput., Electron. Electr. Eng. Appl. (IC2E3)*, Jun. 2023, pp. 1–6.

[4] J. Y. Fam, S. Y. Wong, H. B. M. Basri, M. O. Abdullah, K. B. Lias, and S. Mekhilef, ‘‘Predictive maximum power point tracking for proton exchange membrane fuel cell system,’’ *IEEE Access*, vol. 9, pp. 157384–157397, 2021.

[5] R. Khajuria, R. Lamba, R. Kumar, and S. Yelisetti, ‘‘Application of metaheuristic techniques in optimal parameter estimation of solid oxide fuel cell,’’ in *Proc. Int. Conf. Adv. Energy Res.* Singapore: Springer, 2022, pp. 605–613.

[6] R. Khajuria, R. Lamba, and R. Kumar, ‘‘Model parameter extraction for PEM electrolyzer using honey badger algorithm,’’ in *Proc. IEEE 3rd Int. Conf. Sustain. Energy Future Electr. Transp. (SEFET)*, Aug. 2023, pp. 1–6.

[7] M. Kandidayeni, H. Chaoui, L. Boulon, S. Kelouwani, and J. P. F. Trovão, ‘‘Online system identification of a fuel cell stack with guaranteed stability for energy management applications,’’ *IEEE Trans. Energy Convers.*, vol. 36, no. 4, pp. 2714–2723, Dec. 2021.

[8] A. H. Alqahtani, H. M. Hasanien, M. Alharbi, and S. Chuanyu, ‘‘Parameters estimation of proton exchange membrane fuel cell model based on an improved walrus optimization algorithm,’’ *IEEE Access*, vol. 12, pp. 74979–74992, 2024.

[9] M. Abdel-Basset, R. Mohamed, L. Abdel-Fatah, M. Sharawi, and K. M. Sallam, ‘‘Improved metaheuristic algorithms for optimal parameters selection of proton exchange membrane fuel cells: A comparative study,’’ *IEEE Access*, vol. 11, pp. 7369–7397, 2023.

[10] R. Khajuria, S. Yelisetti, R. Lamba, and R. Kumar, ‘‘Optimal model parameter estimation and performance analysis of PEM electrolyzer using modified honey badger algorithm,’’ *Int. J. Hydrogen Energy*, vol. 49, pp. 238–259, Jan. 2024.

[11] H. Chaoui, M. Kandidayeni, L. Boulon, S. Kelouwani, and H. Gualous, ‘‘Real-time parameter estimation of a fuel cell for remaining useful life assessment,’’ *IEEE Trans. Power Electron.*, vol. 36, no. 7, pp. 7470–7479, Jul. 2021.

[12] R. Khajuria, R. Lamba, and R. Kumar, ‘‘Parameters extraction of pemfc model using evolutionary based optimization algorithms,’’ in *Proc. Int. Conf. Adv. Energy Res.* Singapore: Springer, 2022, pp. 443–451.

[13] A. S. Menesy, H. M. Sultan, A. Korashy, F. A. Banakhr, M. G. Ashmawy, and S. Kamel, ‘‘Effective parameter extraction of different polymer electrolyte membrane fuel cell stack models using a modified artificial ecosystem optimization algorithm,’’ *IEEE Access*, vol. 8, pp. 31892–31909, 2020.

[14] X. Mao, Y. Tian, A. Yang, and G. Zhang, ‘‘Identification of equivalent circuit parameters for proton exchange membrane (PEM) electrolyzer engineering models,’’ *IEEE Access*, vol. 12, pp. 15509–15524, 2024.

[15] Y. Rao, Z. Shao, A. H. Ahangarnejad, E. Gholamalizadeh, and B. Sobhani, ‘‘Shark smell optimizer applied to identify the optimal parameters of the proton exchange membrane fuel cell model,’’ *Energy Convers. Manage.*, vol. 182, pp. 1–8, Feb. 2019.

[16] M. T. Özdemir, ‘‘Optimal parameter estimation of polymer electrolyte membrane fuel cells model with chaos embedded particle swarm optimization,’’ *Int. J. Hydrogen Energy*, vol. 46, no. 30, pp. 16465–16480, Apr. 2021.

[17] H. M. Sultan, A. S. Menesy, S. Kamel, R. A. Turky, H. M. Hasanien, and A. Al-Durra, ‘‘Optimal values of unknown parameters of polymer electrolyte membrane fuel cells using improved chaotic electromagnetic field optimization,’’ *IEEE Trans. Ind. Appl.*, vol. 57, no. 6, pp. 6669–6687, Nov. 2021.

[18] S. Buchaniec, A. Sciazko, M. Mozdzierz, and G. Brus, ‘‘A novel approach to the optimization of a solid oxide fuel cell anode using evolutionary algorithms,’’ *IEEE Access*, vol. 7, pp. 34361–34372, 2019.

[19] J. C. Amphlett, R. F. Mann, B. A. Peppley, P. R. Roberge, and A. Rodrigues, ‘‘A model predicting transient responses of proton exchange membrane fuel cells,’’ *J. Power Sources*, vol. 61, nos. 1–2, pp. 183–188, Jul. 1996.

[20] J. Fu, Q. Xiang, L. Zeng, Y. Zu, H. You, X. Shan, J. Xin, and X. Li, ‘‘A hierarchical optimizing energy management strategy for alleviating degradation in fuel cell hybrid system,’’ *IEEE Access*, vol. 12, pp. 57117–57127, 2024.

[21] Y. Li, M. Liu, Y. Wang, L. Xu, and S. Lei, "Energy management optimization and validation of a hydrogen fuel cell-powered agricultural tractor based on hierarchical dynamic programming," *IEEE Access*, vol. 12, pp. 21382–21401, 2024.

[22] R. Khajuria, R. Lamba, and R. Kumar, "Optimal parameter extraction and performance analysis of proton exchange membrane fuel cell," in *Proc. IEEE Int. Conf. Power Electron., Drives Energy Syst. (PEDES)*, Dec. 2022, pp. 1–6.

[23] G. Xiong, J. Zhang, D. Shi, and X. Yuan, "A simplified competitive swarm optimizer for parameter identification of solid oxide fuel cells," *Energy Convers. Manage.*, vol. 203, Jan. 2020, Art. no. 112204.

[24] B. Mohanty, R. M. Elavarasan, H. M. Hasanien, E. Devaraj, R. A. Turky, and R. Pugazhendhi, "Parameters identification of proton exchange membrane fuel cell model based on the lightning search algorithm," *Energies*, vol. 15, no. 21, p. 7893, 2022.

[25] A. A. El-Fergany, H. M. Hasanien, and A. M. Agwa, "Semi-empirical PEM fuel cells model using whale optimization algorithm," *Energy Convers. Manage.*, vol. 201, Dec. 2019, Art. no. 112197.

[26] A. A. Z. Diab, H. I. Abdul-Ghaffar, A. A. Ahmed, and H. A. Ramadan, "An effective model parameter estimation of PEMFCs using GWO algorithm and its variants," *IET Renew. Power Gener.*, vol. 16, no. 7, pp. 1380–1400, May 2022.

[27] S. I. Selem, H. M. Hasanien, and A. A. El-Fergany, "Parameters extraction of PEMFC's model using manta rays foraging optimizer," *Int. J. Energy Res.*, vol. 44, no. 6, pp. 4629–4640, May 2020.

[28] M. Ćalasan, S. H. E. A. Aleem, H. M. Hasanien, Z. M. Alaas, and Z. M. Ali, "An innovative approach for mathematical modeling and parameter estimation of PEM fuel cells based on iterative Lambert W function," *Energy*, vol. 264, Feb. 2023, Art. no. 126165.

[29] H. Rezk, A. G. Olabi, S. Ferahtia, and E. T. Sayed, "Accurate parameter estimation methodology applied to model proton exchange membrane fuel cell," *Energy*, vol. 255, Sep. 2022, Art. no. 124454.

[30] A. A. El-Fergany, "Electrical characterisation of proton exchange membrane fuel cells stack using grasshopper optimiser," *IET Renew. Power Gener.*, vol. 12, no. 1, pp. 9–17, Jan. 2018.

[31] A. Fathy, M. A. Elaziz, and A. G. Alharbi, "A novel approach based on hybrid vortex search algorithm and differential evolution for identifying the optimal parameters of PEM fuel cell," *Renew. Energy*, vol. 146, pp. 1833–1845, Feb. 2020.

[32] A. A. El-Fergany, "Extracting optimal parameters of PEM fuel cells using salp swarm optimizer," *Renew. Energy*, vol. 119, pp. 641–648, Apr. 2018.

[33] C. Dai, W. Chen, Z. Cheng, Q. Li, Z. Jiang, and J. Jia, "Seeker optimization algorithm for global optimization: A case study on optimal modelling of proton exchange membrane fuel cell (PEMFC)," *Int. J. Electr. Power Energy Syst.*, vol. 33, no. 3, pp. 369–376, Mar. 2011.

[34] E. A. Gouda, M. F. Kotb, and A. A. El-Fergany, "Investigating dynamic performances of fuel cells using pathfinder algorithm," *Energy Convers. Manage.*, vol. 237, Jun. 2021, Art. no. 114099.

[35] M. Abdel-Basset, R. Mohamed, and M. Abouhawwash, "On the facile and accurate determination of the highly accurate recent methods to optimize the parameters of different fuel cells: Simulations and analysis," *Energy*, vol. 272, Jun. 2023, Art. no. 127083.

[36] H. M. Hasanien, M. A. M. Shaheen, R. A. Turky, M. H. Qais, S. Alghuwainem, S. Kamel, M. Tostado-Véliz, and F. Jurado, "Precise modeling of PEM fuel cell using a novel enhanced transient search optimization algorithm," *Energy*, vol. 247, May 2022, Art. no. 123530.

[37] R. Almodfer, M. Mudhsh, S. Alshathri, L. Abualigah, M. A. Elaziz, K. Shahzad, and M. Issa, "Improving parameter estimation of fuel cell using honey badger optimization algorithm," *Frontiers Energy Res.*, vol. 10, May 2022, Art. no. 875332.

[38] M. Kandidayeni, A. Macias, A. Khalatbarisoltani, L. Boulon, and S. Kelouwani, "Benchmark of proton exchange membrane fuel cell parameters extraction with metaheuristic optimization algorithms," *Energy*, vol. 183, pp. 912–925, Sep. 2019.

[39] E. A. Gouda, M. F. Kotb, and A. A. El-Fergany, "Jellyfish search algorithm for extracting unknown parameters of PEM fuel cell models: Steady-state performance and analysis," *Energy*, vol. 221, Apr. 2021, Art. no. 119836.

[40] C. Guo, J. Lu, Z. Tian, W. Guo, and A. Darvishan, "Optimization of critical parameters of PEM fuel cell using TLBO-DE based on Elman neural network," *Energy Convers. Manage.*, vol. 183, pp. 149–158, Mar. 2019.

[41] R. M. Rizk-Allah and A. A. El-Fergany, "Artificial ecosystem optimizer for parameters identification of proton exchange membrane fuel cells model," *Int. J. Hydrogen Energy*, vol. 46, no. 75, pp. 37612–37627, Oct. 2021.

[42] M. Fawzi, A. A. El-Fergany, and H. M. Hasanien, "Effective methodology based on neural network optimizer for extracting model parameters of PEM fuel cells," *Int. J. Energy Res.*, vol. 43, no. 14, pp. 8136–8147, Nov. 2019.

[43] N. Li, G. Zhou, Y. Zhou, W. Deng, and Q. Luo, "Extracting unknown parameters of proton exchange membrane fuel cells using quantum encoded pathfinder algorithm," *Frontiers Energy Res.*, vol. 10, Aug. 2022, Art. no. 964042.

[44] A. Rowe and X. Li, "Mathematical modeling of proton exchange membrane fuel cells," *J. Power Sources*, vol. 102, nos. 1–2, pp. 82–96, 2001.

[45] M. Arif, S. C. P. Cheung, and J. Andrews, "A systematic approach for matching simulated and experimental polarization curves for a PEM fuel cell," *Int. J. Hydrogen Energy*, vol. 45, no. 3, pp. 2206–2223, Jan. 2020.

[46] J. C. Amphlett, R. M. Baumert, R. F. Mann, B. A. Peppley, P. R. Roberge, and T. J. Harris, "Performance modeling of the ballard mark IV solid polymer electrolyte fuel cell: II. Empirical model development," *J. Electrochem. Soc.*, vol. 142, no. 1, pp. 9–15, Jan. 1995.

[47] R. F. Mann, J. C. Amphlett, M. A. I. Hooper, H. M. Jensen, B. A. Peppley, and P. R. Roberge, "Development and application of a generalised steady-state electrochemical model for a PEM fuel cell," *J. Power Sources*, vol. 86, nos. 1–2, pp. 173–180, Mar. 2000.

[48] H. M. Sultan, A. S. Menesy, S. Kamel, A. Selim, and F. Jurado, "Parameter identification of proton exchange membrane fuel cells using an improved salp swarm algorithm," *Energy Convers. Manage.*, vol. 224, Nov. 2020, Art. no. 113341.

[49] X.-S. Yang, M. Karamanoglu, T. O. Ting, and Y.-X. Zhao, "Applications and analysis of bio-inspired eagle strategy for engineering optimization," *Neural Comput. Appl.*, vol. 25, no. 2, pp. 411–420, Aug. 2014.

[50] I. Ahmadianfar, A. A. Heidari, S. Noshadian, H. Chen, and A. H. Gandomi, "INFO: An efficient optimization algorithm based on weighted mean of vectors," *Expert Syst. Appl.*, vol. 195, Jun. 2022, Art. no. 116516.

**RAHUL KHAJURIA** (Graduate Student Member, IEEE) received the B.Tech. degree in electrical engineering from Himachal Pradesh Technical University, Hamirpur, Himachal Pradesh, India, in 2017, and the M.Tech. degree in renewable energy from Shri Mata Vaishno Devi University (SMVDU), Katra, Jammu and Kashmir, India, in 2019. He is currently pursuing the Ph.D. degree in electrical engineering with the Department of Electrical Engineering, Malaviya National Institute of Technology Jaipur (MNIT), Jaipur, India. His research interests include the fuel cell and electrolyzer modeling, energy management in renewable energy integrated microgrids, and meta-heuristic optimization techniques.

**MAHIPAL BUKYA** (Senior Member, IEEE) received the B.Tech. degree in electrical and electronics engineering from BVRIT, JNTU Hyderabad, India, the M.E. degree in electrical engineering from Indian Institute of Science (IISc), Bengaluru, India, and the Ph.D. degree from the Malaviya National Institute of Technology Jaipur (MNIT), Jaipur, Rajasthan, India. He has been a Faculty Member with the Department of Electrical and Electronics Engineering, Manipal Academy of Higher Education, MIT Bengaluru, where he is currently associated as an Assistant Professor (Senior-Scale) and the Assistant Director of IQAC-MIT Blr. His research interests include electrical machines, electrical vehicle (EV), EV cabling networks, EV protection, electromagnetic fields, high voltage engineering, and AI ML applications in EVs.

**RAVITA LAMBA** (Senior Member, IEEE) received the B.Tech. degree (Hons.) in instrumentation and control engineering from the Government Engineering College Bikaner, Bikaner, India, in 2012, and the M.Tech. (Hons.) and Ph.D. degrees in renewable energy from Indian Institute of Technology (IIT) Delhi, New Delhi, India, in 2014 and 2018, respectively. She was an Assistant Professor with the Department of Electrical Engineering, Malaviya National Institute of Technology Jaipur, Jaipur, India, from 2020 to 2024. She was a Visiting Fellow with the University of Exeter, Exeter, U.K., from 2022 to 2023, and the University of South Florida, Tampa, FL, USA, in 2018. She is currently an Assistant Professor with the Department of Hydro and Renewable Energy, Indian Institute of Technology (IIT) Roorkee. Her research interests include modeling and simulation of renewable energy systems, BIPV systems, radiative cooling systems, thermoelectric devices, solar thermal and photovoltaic systems, and machine learning and advanced optimization techniques for renewable based energy systems. She has been awarded the Distinction in Doctoral Research Award for the Ph.D. research work for the year 2018 by IIT Delhi.

**RAJESH KUMAR** (Senior Member, IEEE) received the B.Tech. degree (Hons.) in electrical engineering from the National Institute of Technology (NIT), Kurukshetra, India, in 1994, and the M.E. (Hons.) and Ph.D. degrees in power systems and intelligent systems from the Malaviya National Institute of Technology (MNIT) Jaipur, Rajasthan, India, in 1997 and 2005, respectively. He was a Postdoctoral Research Fellow with the Department of Electrical and Computer Engineering, National University of Singapore (NUS), Singapore, from 2009 to 2011. Since 1995, he has been a Faculty Member with the Department of Electrical Engineering, MNIT Jaipur, where he is currently a Professor. His research interests include intelligent systems, data-driven algorithms and analytics, smart grids, biomedical (signal processing and image processing), and optimization. He has been an Associate Editor of IEEE Access, IEEE Industrial Electronics Technology News (ITeN), *Swarm and Evolutionary Computation*, Elsevier, *IET Renewable Power Generation*, *IET Power Electronics*, *International Journal of Bio-Inspired Computation*, and *CAAI Transactions on Intelligence Technology* (IET). He is appointed as a Distinguished Lecturer of IEEE IAS for 2024 and 2025.