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Badreddine KANOUNI

badreddine.kanouni@univ-setif.dz

University Ferhat Abbas of Setif

Abdelbaset Laib

University of Sciences and Technology Houari Boumediene

Salah Necaibia

Badji Mokhtar University

Abdelbasset Krama

Hamad bin Khalifa University

Abdullah G Alharbi

Princess Nourah bint Abdulrahman University

Hegazy Rezk

Prince Sattam Bin Abdulaziz University

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Precise Parameter Extraction for Proton Exchange Fuel Cells by Mutated Quadratic Interpolation Algorithm

Badreddine kanouni[1*], Abdelbaset Laib[2*], Salah Necaibia[3], Abdelbasset Krama[4], Abdullah G. Alharbi[5] and Hegazy Rezk[6,7*]

[1] Automatic and Intelligent Systems Department, University of Ferhat Abbas Setif 1, Algeria;
[2]Department of Automatic, Faculty of Electrical Engineering, University of Science and Technology Houari Boumediene, Algiers 16111, Algeria.
[3]Electromechanical Systems Laboratory (LSELM), Electrical Engineering Department, Faculty of Technology, Badji Mokhtar University, Annaba, Algeria.
[4]Qatar Environment and Energy Research Institute, Hamad Bin Khalifa University, Doha 34110, Qatar.
[5]Department of Electrical Engineering, College of Engineering, Princess Nourah bint Abdulrahman University, P.O. Box 84428, Riyadh 11671, Saudi Arabia; ABGalharbi@pnu.edu.sa
[6]Department of Electrical Engineering, College of Engineering in Wadi Alddawasir, Prince Sattam bin Abdulaziz University, Saudi Arabia; hr.hussien@psau.edu.sa
[7]Electrical Engineering Department, Faculty of Engineering, Minia University, Egypt

[*]Corresponding authors : Badreddine kanouni, Email: badreddine.kanouni@univ-setif.dz

Abstract

Precision modelling is required to design, control, and optimize proton exchange membrane fuel cells (PEMFCs). A PEMFC constitutes a nonlinear optimization problem defined by seven unknown variables and nonlinear equations. The research proposes combining the mutation phase of Differential Evolution (DE) with Quadratic Interpolation Optimization (QIO) to ascertain PEMFC parameters efficiently. Sum of squared errors (SSE) is suggested as an objective function, which calculated the error between the experimental measures and simulated voltage. The algorithm has been tested utilizing real data for four types of PEMFC: SR-12, Temasek 1 KW, BCS-500 W, and 250 W. The results show that the Mu-QIO have a superiority over the traditional QIO. To validate the superiority of the proposed algorithm, it is compared with the traditional QIO and well known algorithms.The robust correlation between the simulated and observed polarization curves corroborates the method's capacity to estimate unknown parameters. Furthermore, statistical performance metrics indicate the algorithm's consistent supremacy in all evaluated settings, highlighting its robustness and adaptability.

Keywords: Fuel cells, parameter identification, metaheuristics algorithms, Quadratic Interpolation Optimization.

1. Introduction

The tremendous revolutions that are occurring in industrialisation, civilisation, and the economy are causing an increase in the need for electrical energy all over the world [1,2]. on of these fuels is restricted due to the severe defects they possess, which include global warming, emissions of carbon dioxide, and harmful pollutants [3,4]. In order to properly deal with the growing demand for electrical energy, it is vital to make use of energy supplies that are both sustainable and favourable to the environment [2]. The usage of renewable energy sources is beginning to gain favour and is becoming more common [5]. The sustainability of the environment, the lowest possible carbon emissions, and the inexhaustibility of these sources are all significant advantages and contributions.Over the course of the last several decades, fuel cells (FCs) have garnered the interest of a number of companies and researchers due to the fact that their operation is not harmful to the environment and that they generate increased efficiency[2]. In a short amount of time, fuel cells are able to convert the chemical energy that is produced by the reaction of oxygen and hydrogen, or the air around them, into electricity[6]. fhosphoric acid fuel cells, molten carbonate fuel cells, solid oxide fuel cells, direct methanol fuel cells, alkaline fuel cells, and reversible fuel cells are some of the different types of fuel cells [7,8], Proton exchange membrane fuel cells (PEMFC) are the most popular type of fuel cell due to their low operational temperature (30°C-100°C), durability, environmental sustainability, high rate of efficiency (40–50%), and rapid startup capabilities [8,9]. PEMFC is suitable for a wide scope of applications, including transportation, additional power units, distributed generation, and space attempts [2].

In addition to this, the PEMFC is a nonlinear system that contains a very large number of complex internal reactions. Multiple mechanisms, including mass transfer, electrochemical reactions, heat transmission, and electric charge transmission, are utilised in the operation of a single portable electrochemical fuel cell (PEMFC). Consequently, the PEMFC model is complicated as a result of the simultaneous occurrence of all of these events, and it is hard to foresee the attributes of the PEMFC [10]. A mathematical model that is accurate is required in order to appreciate the numerous processes that are involved in the evaluation of the performance of PEMFCs under a variety of circumstances and to enhance the design of the device. In order to enhance the longevity and resiliency of PEMFCs, scientists and researchers are continuously

studying various methods. [11–13]. One of these methods involves the utilisation of sophisticated modelling and simulation tools, which are crucial for comprehending the intricate processes that occur within PEMFCs. Using mathematical models, researchers are able to enhance operating conditions, predict the lifetime of PEMFCs, and investigate the factors that influence the efficacy and degradation of the mathematic model [14].

The mathematical model of PEMFC is essential for predicting and modeling its performance in energy systems or other applications. This model is crucial for evaluating the performance of PEM fuel cells under various operating circumstances. It may also improve the performance of PEMFC across several domains, including connection with renewable energy sources, managing energy, battery storage, and microgrids [2]. Furthermore, the model facilitates performance monitoring and ensures the effective regulation and usage of the PEMFC within any energy system. Consequently, a precise model that simulates real-time PEMFC functioning is essential. To do this, it is necessary to precisely identify the unidentified parameters since they considerably affect the performance of the PEMFC. This behavior is often discerned using polarization characteristics, especially I-V. Amphlett [15] presented a semi-empirical mathematical model to define the behavior of PEMFC, including several formulas that reflect the numerous physical and chemical processes that influence its functioning. Consequently, researchers globally have a significant problem in developing an appropriate model for PEMFC because of its very non-linear characteristics. Nevertheless, the PEMFC mathematical model is regarded as complicated, multivariate, and multimodal, making it difficult to govern and forecast its performance under varying situations [16].Furthermore, the model incorporates several unknown characteristics that control the PEMFC's effectiveness, and each one which affects the others. Minor fluctuations in these factors may substantially affect output performance. Moreover, manufacturer data sheets lack information on these particular features. As a result, an appropriate parameter extraction method is crucial for constructing a precise model that allows for efficient online control and performance evaluation under diverse situations, including variable loads, temperatures, and gas flow rates [17,18]. A mathematical model is used to show how the PEMFC works, and its regulating parameters are based on well-known physical and electrochemical laws. To make the model fit the experimental data, several methods for estimating parameters are utilized to change unknown elements that are relevant to the model [19].

The polarization behavior of a PEMFC is what mostly determines how well it works. This may be found by solving a set of voltage equations in a PEMFC model. These equations account for various voltage losses, characterized by several unknown variables that considerably influence the accuracy of the polarization curve. For accurate modeling of PEMFCs, a complete parameter identification method is essential to ensure that the simulated polarization characteristics closely match experimental data.

Many optimization-based methods to correctly find PEMFC parameters. The dependability, consistency, and simplicity of these methods are well known. [20]. A lot of study has been done to find the best sets of parameters utilizing modern metaheuristic and hybrid algorithms. Some well-known examples include the hybrid marine predator optimizer (MPO) and political optimizer (PO)[4], enhanced chaotic gray wolf optimization (IGWO) [21], TLBO-DE using Elman Neural Network [22], shuffled multi-simplex search algorithm [23], and Chaotically based-bonobo optimizer [24].

Analyzing a PEMFC-like circuit using a multiverse optimizer [25]. A total of seven factors were considered for this research. Comparable findings from several authors indicated a range of optimization parameters that ensure convergence [26]. The various methodologies were classified, highlighting evolutionary strategies, swarm dynamics, and natural phenomena in [27] to evaluate several metaheuristic microgrid optimization approaches. Furthermore, Adaptive sparrow search methodologies were examined to assess the discrepancy between the measured and determined voltage to minimize the SSE [28]. The author in [29] presents an effective self-adaptive bonobo Optimizer (Sabo) for determining the unknown parameters of the proton exchange membrane fuel cell (PEMFC), accompanied by a comparison with other robust techniques. An enhanced adaptive guided differential evolution (AGDE) method is introduced in [30] by including roulette wheel selection (RWS) optimization-based fitness-distance balance (RFDB) and Levy flight (LF) techniques, referred to as LRFDB-AGDE. The amalgamation of several improvement tactics aims to optimize the mutation mechanism architecture of the AGDE algorithm, hence improving the local and global search capabilities of the LRFDB-AGDE algorithm. The author [2] presents an innovative hybrid methodology using a weighted mean of vectors and the Nelder-Mead (INFONM) technique for the extraction of parameters in PEM fuel cells. An optimization issue is

formulated via a SSE, to assess the NedStack PS6, BCS 500 W, 250 W, and Ballard Mark V fuel cell stacks.

Each optimization approach has distinct strengths and attributes, enhancing the variety and progress of the optimization landscape for PEMFC parameter discovery. Nonetheless, many approaches have certain constraints, such as sluggish convergence, vulnerability to local minima, or restricted accuracy. Consequently, a need persists for a high-performance method proficient in precisely and effectively estimating the unknown parameters of PEMFC models.

Motivated by these challenges, the authors propose a novel hybrid technique combining the recently developed Quadratic Interpolation Optimization (QIO) method with Differential Evolution (DE) mutation phase. This novel hybrid approach (Mu-QIO) has been designed to use the advantage of the exploration of DE and the local refinement efficiency of QIO. The proposed algorithm is applied for the first time for parameter identification of PEMFC.

In this paper a novel hybrid Mu-QiO is proposed for parameter identification of PEMFC. The proposed algorithm uses the experimental data of the polarization curve and helps build an accurate mathematical model of PEMFC by identifying the unknown parameter. The objectives of the paper are presented as follows:

- A hybrid Mu-QIO (Mutated Quadratic Interpolation Optimization) is proposed, which combines the QIO algorithm and mutation phase from DE algorithm.
- Evaluating the proposed algorithm in terms of the efficacy and precision of identifying the unknown parameter.
- Test the hybrid algorithm on several commercial types of PEMFC, and compare it with the traditional one in terms of convergence, curves, and statistical analysis.
- Evaluating the Mu-QIO under pressure and temperature variation.

The structure of this paper is outlined as follows: Section 2: Modeling of the PEMFC and explanation of the objective function. Section 3: Explain the suggested hybrid methodology. Section 4 will discuss the results. The conclusion is situated in Section 5.

2. Modeling of proton exchange MFC and the objective function

2.1. Mathematical modeling of PEMFC

A PEMFC is comprised of two electrodes, namely an anode and a cathode, which are separated from one another by a thin solid proton-conducting membrane [31]. Fig.1 depicts the chemical reactions that take place due to the presence of these electrodes. This is an example of a method that may be used to describe the overall response that takes place inside a PEMFC:

$$H_2 + {}^1/_2\, O_2 \xrightarrow{tr} H_2O + Electricity + Heat \quad (1)$$

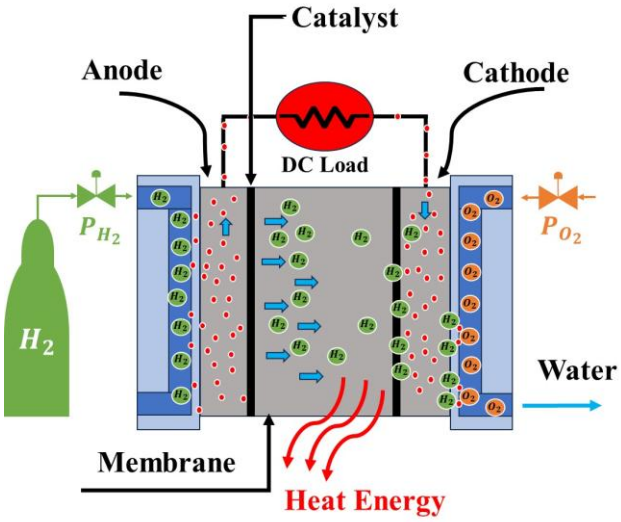


Fig.1 Proton exchange MFC schematic.

It is impossible to determine the electrical potential or current that is generated by a single fuel cell. As a consequence of this, numerous fuel compartments in a design are frequently connected in series in order to increase the magnitude of the electrical potential. In the case of PEMFC cells that are connected in series, the endpoint stack voltage (V_{SE}) is calculated by multiplying the number of cells (n) by the voltage of a single cell. This is represented as follows [32][33]:

$$V_{SE} = n \times (\mathrm{E}_{Nr_cell} - V_{act_cell} - V_{oh_cell} - V_{con_cell}) \quad (2)$$

The terminal voltage of one single PEMFC is inferior to the theoretical voltage ((E_{Nr_cell}) due to three electrical potential reductions: activation voltage loss (V_{act_cell}), ohmic voltage loss (V_{oh_cell}), and concentration voltage loss (V_{con_cell}) [33].

The (E_{Nr_cell}) equation ties cell voltage with temperature (T_{FC}) and the partial pressures of hydrogen P_{H_2} and oxygen (P_{O_2}) gases, as expressed below:

$$E_{nrs} = 1.229 - 0.85 \times 10^{-3}(T_{FC} - 298.15) + 4.3085 \times 10^{-5} \times T_{FC} \times \left[ln\left(P_{H_2}\right) + {}^{1}/_{2}\ ln\left(P_{O_2}\right)\right] \quad (3)$$

$$P_{O_2} = Rh_c P_{H_2O}^{sat}\left[\left(exp\left(\frac{4.192(i_{FC}/A)}{T_{FC}^{1.334}}\right) \times \frac{Rh_c P_{H_2O}^{sat}}{P_c}\right)^{-1} - 1\right] \quad (4)$$

$$P_{H_2} = 0.5Rh_a P_{H_2O}^{sat}\left[\left(exp\left(\frac{1.635(i_{FC}/A)}{T_{FC}^{1.334}}\right) \times \frac{Rh_a P_{H_2O}^{sat}}{P_a}\right)^{-1} - 1\right] \quad (5)$$

Here, P_c and P_a Stands for the input negative and electrode pressures, respectively. The relative humidity on the positive and negative electrodes is represented by Rh_a and Rh_c, respectively. A is the membrane's active region, while i_{FC} is the cell current.

The definition of the water saturation pressure, which is represented by the symbol $P_{H_2O}^{sat}$, is represented as follows:

$$log_{10}\left(P_{H_2O}^{sat}\right) = 2.95 \times 10^{-2}(T_{FC} - 273.15) - 9.18 \times 10^{-5}(T_{FC} - 273.15)^2 + \cdots$$

$$\ldots + 1.44 \times 10^{-7}(T_{FC} - 273.15)^3 - 2.18 \quad (6)$$

The three voltage losses: activation voltage (V_{act_cell}), ohmic voltage (V_{oh_cell}), and concentration voltage (V_{con_cell}) are represented in Eq. 7, Eq.8, and Eq. 11 [13,33,34].

$$V_{act_cell} = \varepsilon_1 + \varepsilon_2 T_{FC} + \varepsilon_3 T_{FC} ln\left(\frac{P_{O_2}}{5.08\times10^6 exp\left(\frac{-495}{T_{FC}}\right)}\right) + \varepsilon_4 T_{FC} ln(i_{FC}) \quad (7)$$

$$V_{oh_cell} = i_{FC}(R_c + R_m) \quad (8)$$

$$R_m = \frac{\rho_m\, l}{A} \quad (9)$$

$$\rho_m = \frac{181.6\left[1+0.03\left(\frac{I_{FC}}{A}\right)+0.062\left(\frac{T_{FC}}{303}\right)^2\left(\frac{i_{FC}}{A}\right)^2\right]}{\left[\lambda-0.634-3\left(\frac{i_{FC}}{A}\right)\right]\times exp\left[4.18\left(\frac{T_{FC}-303}{T_{FC}}\right)\right]} \quad (10)$$

$$V_{con_cell} = -\beta\ ln\left(1 - \frac{J}{J_{max}}\right) \quad (11)$$

The semi-experimental components are denoted by the letters $\varepsilon_{1,2,3,4}$. R_c Is the barrier to proton transfer across the membrane, and R_m Is the membrane's corresponding obstruction to proton transfer, as described in Eq.9 [33].

l denotes the membrane's width and ρ_m Signifies the membrane's unique resistivity, as seen in Eq. 10; λ is an empirical quantity that necessitates estimation. β represents the parametric coefficient, J denotes the current density, and J_{max} Signifies the maximum current density [35].

From the PEMFC mathematical modeling, it is evident that $\varepsilon_{1,2,3,4}$ λ, β, and R_c These are the indeterminate parameters. Therefore, it is evident that proper identification of these parameters is essential for establishing an accurate PEMFC model. Consequently, this study proposes a parameter extraction approach using a hybrid Mu-QIO algorithm, which efficiently extracts unknown parameters.

2.2.Objective function

The primary constraints in creating a precise PEMFC model are:

1. There is an absence of data for various parameters utilized in the mathematical model on fuel cell data sheets.
2. Slight variations in these parameter values significantly affect the polarization characteristics.
3. Any erroneous values of these parameters can substantially distort the simulated polarization characteristics from the actual ones.

Consequently, to construct a precise PEMFC model by the mathematical modeling, the parameters. $\varepsilon_{1,2,3,4}$ λ, β, and R_c It must be correctly determined.

The model's parameters can be derived from the observed data using the SSE as an objective function for both the measured (V_{SE_mus}) and estimated (V_{SE_est}) datasets. The fundamental elements of optimization techniques are the objective function and the constraints on parameters. Table 1 outlines the theoretical limitations of choice parameters [36]. The primary goal function is to minimize the SSE. The formula for analyzing SSE is computed as follows [20][37]:

$$F_{oj} = \min\left(SSE\right) = \left(\sum_{i=1}^{k}\left[V_{SE_mus} - V_{SE_est}(X, i_{FC})\right]^2\right) \quad (12)$$

k represents the quantity of data readings, X denotes the collection of unidentified parameters that need identification. While the extraction procedures are represented in the following figure

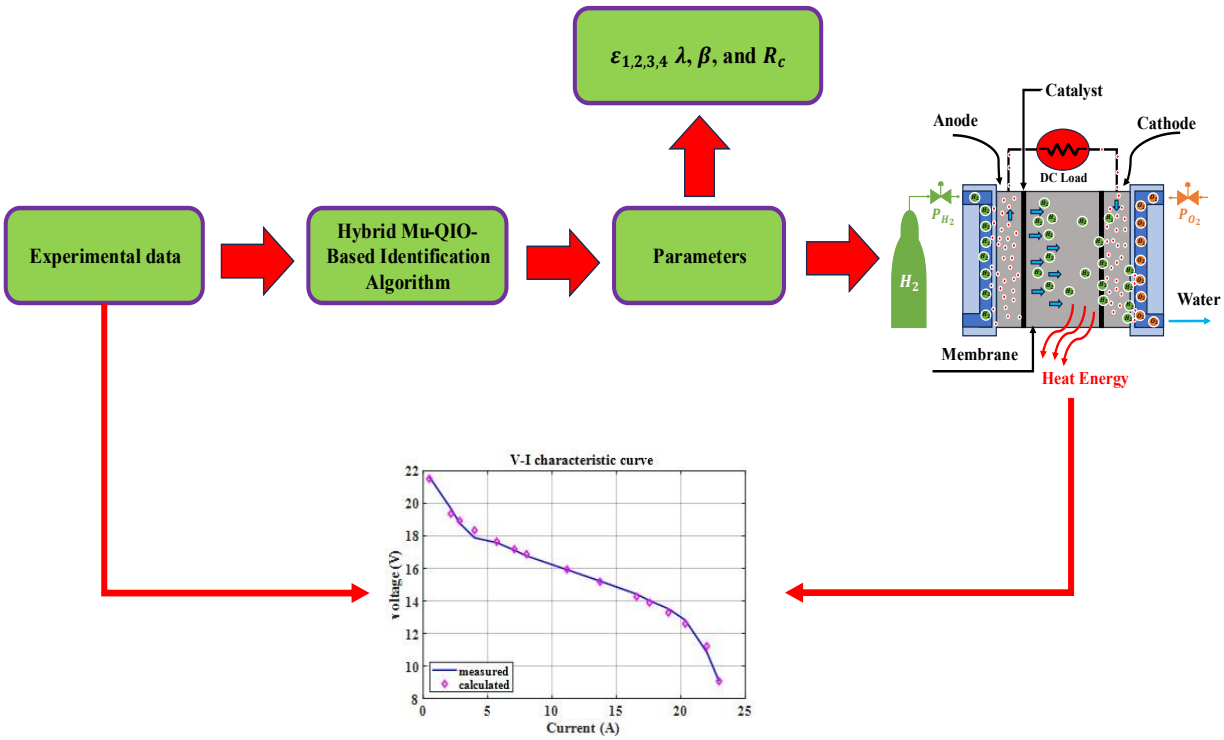


Fig.2 Proton exchange MFC Parameter extraction procedures.

Table. 1 Boundaries of the unknown parameters

Unknown parameter	Upper bound	Lower bound
ε_1	-1.19969	-0.8532
ε_2	0.001	0.005
ε_3	$3.6\text{x}10^{-05}$	$9.8\text{x}10^{-05}$
ε_4	$-2.6\text{x}10^{-04}$	$-0.954\text{x}10^{-04}$
λ	10	24
β	0.0136	0.5
R_c	0.0001	0.0008

3. Proposed Mutation - Quadratic Interpolation Optimization

3.1 Quadratic Interpolation Optimization (QIO)

QIO originates from mathematics, particularly the recently introduced generalized quadratic interpolation (GQI) technique. The QIO employs the GQI approach as an effective search

mechanism for addressing diverse optimization challenges. This search mechanism employs exploration and exploitation strategies, whereby the minimizer from the GQI method assists the QIO algorithm in probing potential areas in unexplored territories and leveraging optimal solutions in advantageous locations. This sub-section starts with delineating the mathematical definition of QIO.

3.1.1 Quadratic interpolation method

The essential framework for quadratic interpolation is outlined as follows: $L(x)$, the quadratic interpolant of the cost function ($f(x)$), is represented as [38]:

$$L(x) = \alpha x^2 + \beta x + \sigma \qquad \alpha, \beta, \sigma \in R \tag{13}$$

Suppose the cost function possesses three points $P_i\big(x_i, f(x_i)\big)$, $P_i\left(x_j, f\big(x_j\big)\right)$, and $P_k\big(x_k, f(x_k)\big)$, where $a \le x_i < x_j < x_k \le b$

Based on the interpolation criteria, the value of the cost function is equivalent to L(x) at the interpolation points. x_i, x_j, and x_k, as expressed:

$$\begin{cases} L(x_i) = \alpha {x_i}^2 + \beta x_i + \sigma = f(x_i) \\ L(x_i) = \alpha {x_j}^2 + \beta x_j + \sigma = f\big(x_j\big) \\ L(x_k) = \alpha {x_k}^2 + \beta x_k + \sigma = f(x_k) \end{cases} \tag{13}$$

To get the minimum of L(x), differentiate Eq. (13) and equate it to 0. The minimizer x* may be found by [38]:

$$x^* = -{\beta}/{2\alpha} \tag{14}$$

While the expressions of α, and b are solved as follows:

$$\begin{cases} \alpha = \frac{(x_J - x_k) f(x_i) + (x_k - x_i) f\big(x_j\big) + (x_i - x_j) f(x_k)}{(x_J - x_k)(x_k - x_i)(x_i - x_j)} \\ \beta = \frac{({x_j}^2 - {x_k}^2) f(x_i) + ({x_k}^2 - {x_i}^2) f\big(x_j\big) + ({x_i}^2 - {x_j}^2) f(x_k)}{(x_J - x_k)(x_k - x_i)(x_i - x_j)} \end{cases} \tag{15}$$

Meanwhile, it is possible to define the quadratic interpolation polynomial L(x) as:

$$L(x) = \frac{(x - x_j)(x - x_k)}{(x_i - x_j)(x_i - x_k)} f(x_i) + \frac{(x - x_i)(x - x_k)}{(x_j - x_i)(x_j - x_k)} f\big(x_j\big) + \frac{(x - x_i)(x - x_j)}{(x_k - x_i)(x_k - x_j)} f(x_k) \tag{16}$$

Quadratic interpolation is often used to estimate the minimum of $f(x)$. In actual applications of minimization problems, there are no explicit criteria for selecting three points. However, the wrong selection of points may result in constructing an upward-opening parabola, yielding a maximizer instead of a minimizer. The necessity to pick three locations for defining a downward-opening parabola presents issues related to time efficiency and efficacy.

A GQI technique has been developed and described in ref [38] to tackle this problem and satisfy the need for a more comprehensive solution.

3.1.2 Exploration strategy

The GQI approach is used to ascertain the exploration strategy within the QIO. Two participants were randomly selected from the existing population to discover prospective locations, and the present individuals were collaboratively used in the GQI approach to discover prospective locations. During exploration via the GQI approach, the location of the present individual is updated as follows [38]:

$$v_i(t+1) = x^*_{i,rand1,rand2}(t) + \omega_1.\left(x_{rand3}(t) - x^*_{i,rand1,rand2}(t)\right) + \cdots$$

$$\ldots + round(0.5.(0.05) + r_1)).log\left({}^{r_2}/_{r_3}\right) \quad (17)$$

$$x^*_{i,rand1,rand2}(t) = GQI\left(x_i(t), x_{rand1}(t), x_{rand2}(t), fit\left(x_i(t)\right), fit\left(x_{rand1}(t)\right), fit\left(x_{rand2}(t)\right)\right) \quad (18)$$

Where x_{rand1}, x_{rand2}, and x_{rand3} denote the placements of several individuals randomly selected from the current population, $(r_1, r_2, r_2) \in [0,1]$ and $fit(\ldots)$ Signifies the function value.

To ensure that the technique executes exploration, balances exploration and exploitation, and converges to the optimal solution, the exploration weight w1 is crucial, represented as follows [38]:

$$\omega_1 = 3n_1 b \quad (19)$$

$$b = 0.7a + 0.15a\left(cos\left({}^{5\pi t}/_{T}\right) + 1\right) \quad (20)$$

$$a = \cos\left({}^{t\pi}/_{2T}\right) \quad (21)$$

n_1, t, T are conventional normal distribution, the iteration, and T is the maximum number of iterations.

3.1.3 Exploitation phase

Exploitation seeks to accelerate convergence towards the global optimum solution. In the exploitation phase of QIO, two randomly selected individuals from the present population, along with the best individual identified thus far, are utilized in the GQI approach to generate an improved solution. Consequently, when the QIO facilitates exploitation, the individual's current status is updated as follows [38]:

$$v_i(t+1) = x^*_{best,rand1,rand2}(t) + \omega_2.\left(x_{best}(t) - round(1+rand).\frac{Ub-Lb}{Ub^{rD}-Lb^{rD}}.x_i^{rD}(t)\right) \quad (22)$$

$$x^*_{best,rand1,rand2}(t) = GQI\left(x_{best}(t), x_{rand1}(t), x_{rand2}(t), fit\left(x_{best}(t)\right), fit\left(x_{rand1}(t)\right), fit\left(x_{rand2}(t)\right)\right) \quad (23)$$

$$\omega_2 = 3\left(1 - \frac{t-1}{T}\right)n_2 \quad (24)$$

When n_2 is a normal distribution, and $rD \in [1, d]$, Lb^{rD} and Ub^{rD} Represent the lower and upper limits at the (rD_th) dimension. ω_2 It is the exploitation weight, serving as an adaptable coefficient.

3.1.4 Mutation strategy

Differential Evolution (DE) functions in two phases: initiation and evolution. The population is initially generated randomly; then, during the evolution phase, it experiences mutation, crossover, and selection processes, which are repeated until the termination criteria are met. [39].

One of the most crucial stages we need in the hybridization process is the mutation operation established in this study.

Following exploitation and exploration, a mutation is performed to create a new vector called a mutation vector.

In mutation, a mutant vector v_i is generated for each target vector $x_i(t)$ It is chosen from the current population as the best cost vector as follows:

$$v_i(t+1) = x^*_{rand1}(t) + +F.\left(x^*_{rand2}(t) + x^*_{rand3}(t)\right) \quad (25)$$

Where *F* represents the scaling factor, and its value is *F* varies from 1 to 0.

Upon the completion of exploration and exploitation methods, the position of the i[th] individual is revised by the following equations:

$$x_i(t+1) = \begin{cases} x_i(t) & fit\left(x_i(t)\right) \le fit\left(v_i(t+1)\right) \\ v_i(t+1) & fit\left(x_i(t)\right) > fit\left(v_i(t+1)\right) \end{cases} \quad (26)$$

The individual's present position is substituted with its candidate position if the fitness value of the candidate position is better than the existing one. If not, it stays the same. The pseudo-code is presented, and the Flowchart of the proposed Mu-QIO is presented in Fig. 3

Algorithm pseudo-code of the proposed Mu-QIO

Set parameters n and T

Randomly initialize the population. $x_i (i = 1, \dots, n$ and evaluate their fitness fit_i , and $x_{best} It$ is the best solution found so far.

While the stopping condition is not satisfied, **do**

For each $i = 1{:}n$

Randomly choose two individuals. $r_{n1} \neq r_{n2} \neq i$ from the population

If $rand > 0.5$

For each position component, $j = 1{:}d$ **do**

Obtain the minimizer x_j^{j*} of the GQI function with x_j^j , x_{rand1}^j , and x_{rand2}^j using Eq.18

End For

Randomly choose on individual $rand3 \neq rand1, rand3 \neq rand2$ and $rand3 \neq i$ from the population

Perform exploration strategy for the ith individual using Eq. 17

Else

For each position component, $j = 1{:}d$ **do**

Obtain the minimizer x_j^{j*} of the GQI function with x_{best}^j , x_{rand1}^j , and x_{rand2}^j using Eq.23

End For

Perform exploration strategy for the ith individual using Eq. 22

For each position component, $j = 1{:}d$ **do**

Select three random solutions,

Check the boundary of the new vector position.

End for

Perform mutation strategy using Eq. 25

Evaluate the ith individual using Eq. 26

End For

Update the best solution found so far. x_{best}

End while

Return

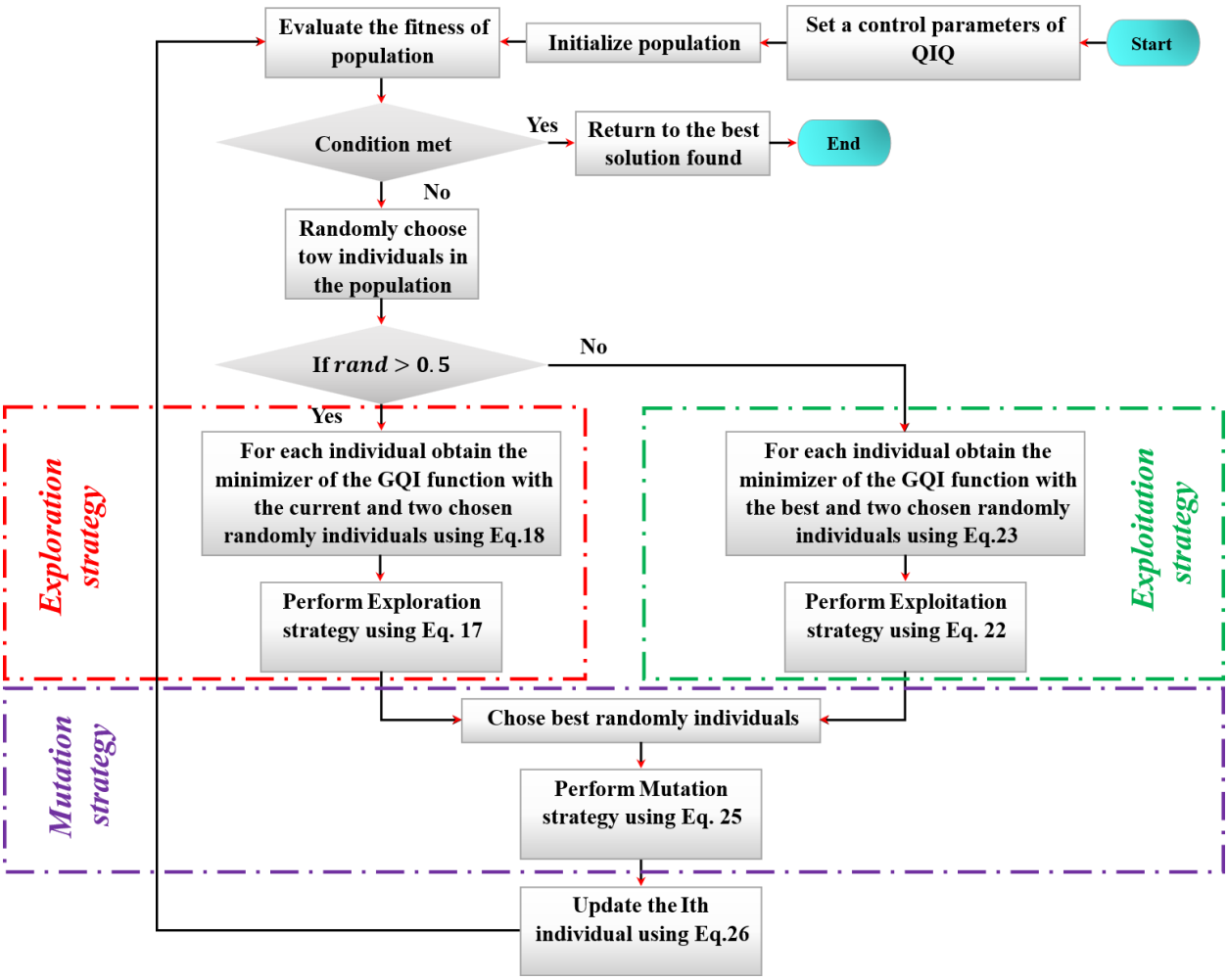


Fig. 3: Flowchart of the proposed Mu-QIO

4 Results and discussion

This paper introduces the Mu-QIO technique for extracting unidentified variables in PEMFCs. Four separate examples are analyzed using publicly available data sheets from PEMFC stacks, specifically: 250 W, BCS-500 W, Temasek 1 KW, and SR-12, to evaluate the efficacy of the Mu-QIO method. The datasheet of these PEMFCs is detailed in Table 2 and sourced from [40] [41]. The research literature presents the experimental data for these fuel cells as polarization curves. The required experimental data, including voltage and power at various currents, are needed to delineate the polarization features. This data is used to validate the results obtained from the proposed Mu-QIO approach, emphasizing the reduction of the disparity between experimental and predicted polarization characteristics..

This study compares the results obtained by employing Mu-QIO for all PEMFC stacks with the conventional QIO. and the techniques from published work. The purpose of this comparison is to demonstrate that Mu-QIO is genuine authenticity, for parameter extraction in PEM fuel cells, the primary advantages of this novel hybrid method are improved accuracy, accelerated convergence, and the avoidance of local minima.

Table.2. Proton exchange MFC datasheet

PEMFC parameters	250W	BCS 500 W	Temasek 1Kw	SR-12
n	24	32	20	48
A	27	64	150	62.5
l	127	178	51	25
T_{FC}	343.15	333	323	323
P_{O_2}	1-05	0.2095	0.5	0.2095
P_{H_2}	1-03	1	0.5	1.47628

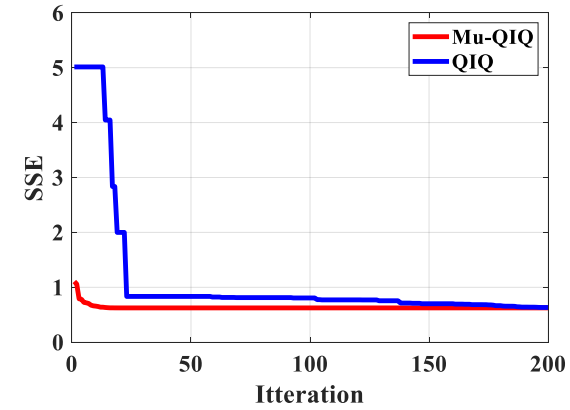
4.1 Estimate the seven unknown parameters

This subsection applies the suggested Mu-QIO for extracting the unidentified characteristics of 250 W, BCS-500 W, Temasek 1 KW, and SR-12.

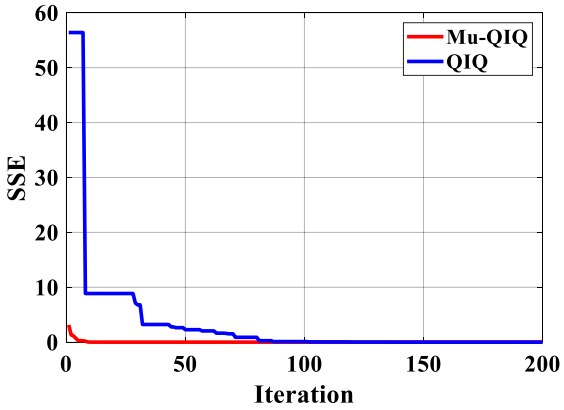
A comparison of the four fuel cell stacks using Mu-QIO and the traditional Mu-QIO is shown in Tables 3, 4, 5, and 6.

Fig. 4 and 5 illustrate the convergence curves and the correlation between the estimated polarization characteristics derived by Mu-QIO and the experimental polarization characteristics.

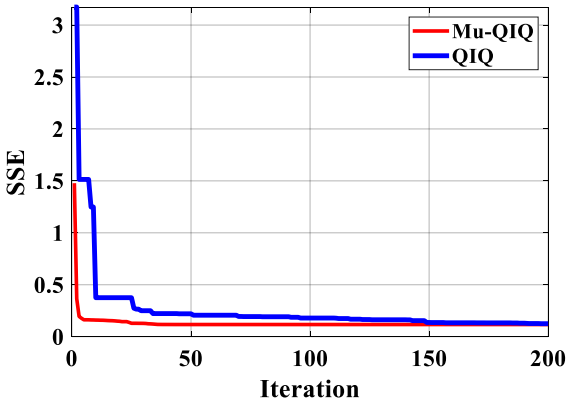
The convergence curve in Fig. 4 for the four PEMFC types illustrates that the Mu-QIO method has a superior convergence rate to the traditional QIO algorithm, efficiently addressing parameter extraction issues. Furthermore, the current-voltage (I-V) and polarization curves generated by Mu-QIO are juxtaposed with the experimentally observed data of the 250 W, BCS-500 W, Temasek 1 KW, and SR-12, as seen in Fig. 5 (a-d). The figure demonstrates that a strong correlation between the experimental and estimated I-V curves shows the correctness of the suggested strategy. Furthermore, Fig. 6 illustrates the change of various forms of voltage loss experienced in the four PEMFCs, using the predicted values derived from the model employing the suggested Mu-QIO in relation to the cell current.



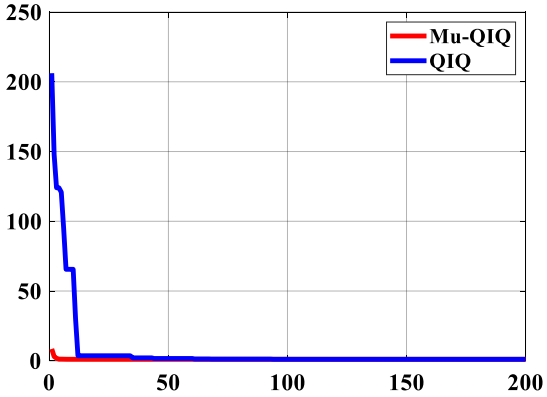
(a)



(b)

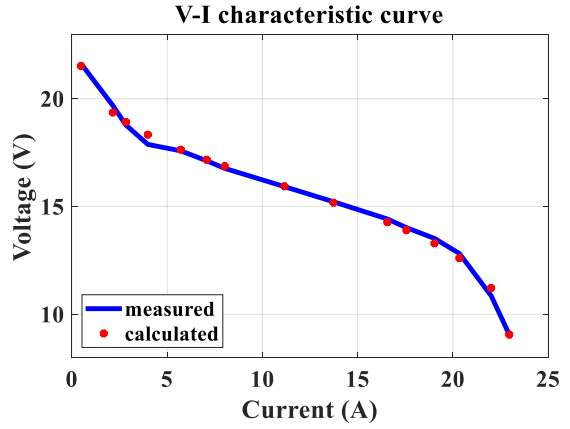


(c)

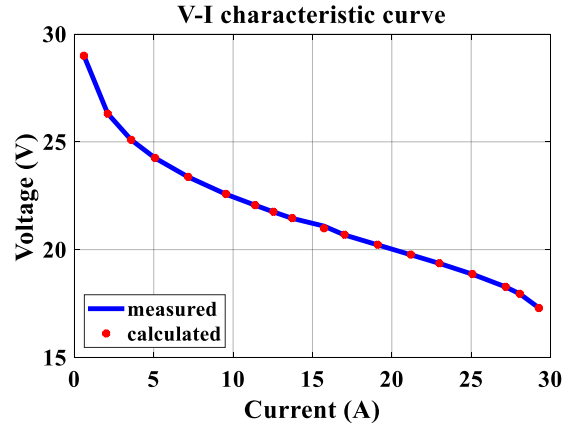


(d)

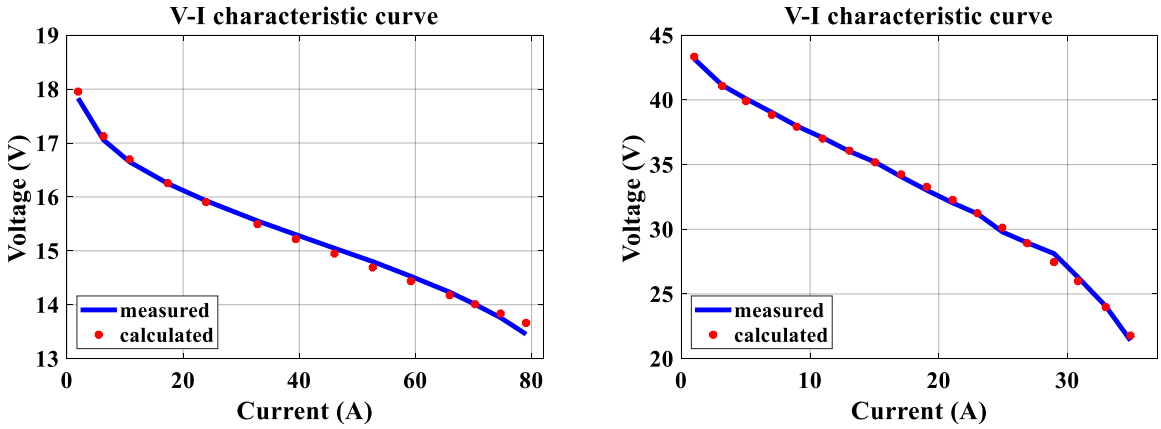
Fig.4 Convergence curve: (a) 250 W, (b) BCS-500 W, (c) Temasek 1 KW, (d) SR-12



(a)

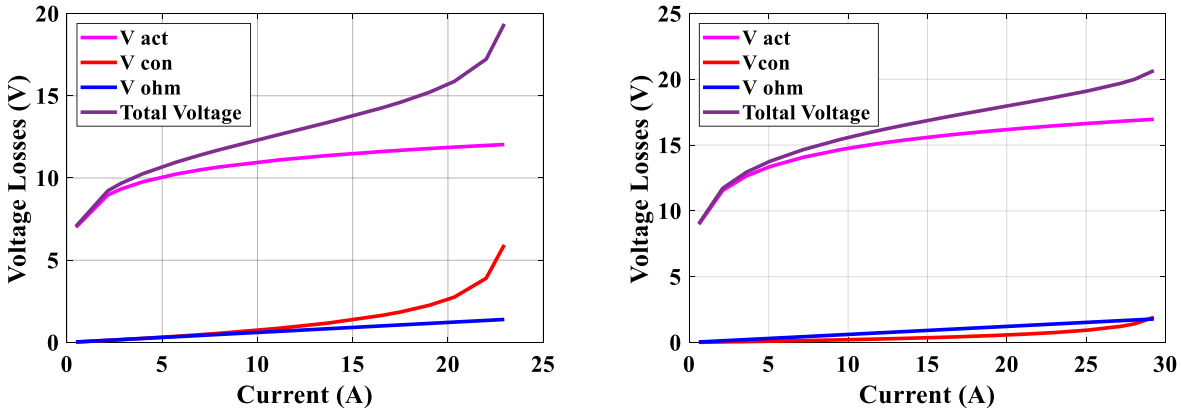


(b)

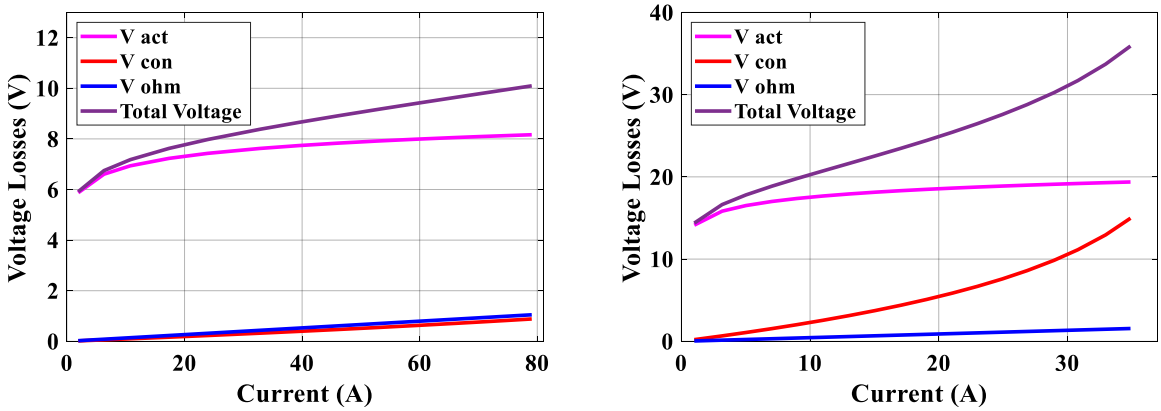


(c) (d)

Fig.5 V-I polarization curves : (a) 250 W, (b) BCS-500 W, (c) Temasek 1 KW, (d) SR-12



(a) (b)



(c) (d)

Fig.6 Voltage losses for : (a) 250 W, (b) BCS-500 W, (c) Temasek 1 KW, (d) SR-12.

Table.3 Estimated parameters using Mu-QIO and conventional QIO for 250 W PEMFC.

Algo	SSE	ε_1	ε_2 x10^{-3}	ε_3 x10^{-5}	ε_4 x10^{-4}	λ	β	R_c x10^{-4}
Mu-QIO	**0.624711**	**-0.866327**	**2.887256**	**9.516569**	**-1.572036**	**23.999982**	**0.055058**	**1.000036**
QIO	0.63263	-0.990698	2.688336	5.493024	-1.580433	23.999597	0.054354	1.167377
MMRFO[42]	0.6420829	-1.06414	3.244598	6.73197	-1.56013	18.36909	0.05452	2.26552
MRFO[42]	0.645217942	-1.11417	2.85814	7.74401	- 1.46370	21.93193	0.05038	2.14608
TGA[42]	0.7496	- 1.1914	4.112	6.057	- 1.709	18.68	0.0544	4.852

Table 4 Estimated parameters using Mu-QIO and conventional QIO for BCS-500 W PEMFC.

Algo	**SSE**	ε_1	ε_2 x10^{-3}	ε_3 x10^{-5}	ε_4 x10^{-4}	λ	β	R_c x10^{-4}
Mu-QIO	**0.011556**	**-1.164702**	**3.378825**	**5.302621**	**-1.92703**	**22.779539**	**0.016230**	**2.735926**
QIO	0.011726	-0.958338	3.199268	8.140711	-1.924862	22.784053	0.016108	2.944202
P-DSO[43]	0.0117	- 1.1042	3.3160	6.0640	- 1.93005	13.4649	0.0161	1.0894
MMRFO[42]	0.0115746	- 1.14206	3.14415	4.85346	- 1.92980	21.071183	0.0161669	1.162537
MRFO [42]	0.01295	- 1.08700	5.88945	7.56310	- 1.07567	14.49902	0.17965	5.08060

Table.5 Estimated parameters using Mu-QIO and conventional QIO for Temasek 1 KW PEMFC.

Algo	**SSE**	ε_1	ε_2 x10^{-3}	ε_3 x10^{-5}	ε_4 x10^{-4}	λ	β	R_c x10^{-4}
Mu-QIO	**0.117106**	**-1.163531**	**3.387700**	**4.333906**	**-0.954002**	**10.003669**	**0.102113**	**1.001238**
QIO	0.125235	-1.0285323	3.085284	5.103809	-0.954749	11.901037	0.125473	1.122170
MMRFO[42]	0.79099	- 0.98118	3.72823	6.421681	- 2.30425	13.01261	0.066827	1.00015
MRFO [42]	0.79382	- 1.176938	4.57888	8.81969	- 1.72465	17.79465	0.12465	7.54113
SSA[42]	0.796814	− 1.1336	4.1130	0.6004	− 2.231	21.5365	0.1025	0.0001

Table 6 Estimated parameters using Mu-QIO and conventional QIO for SR-12 PEMFC.

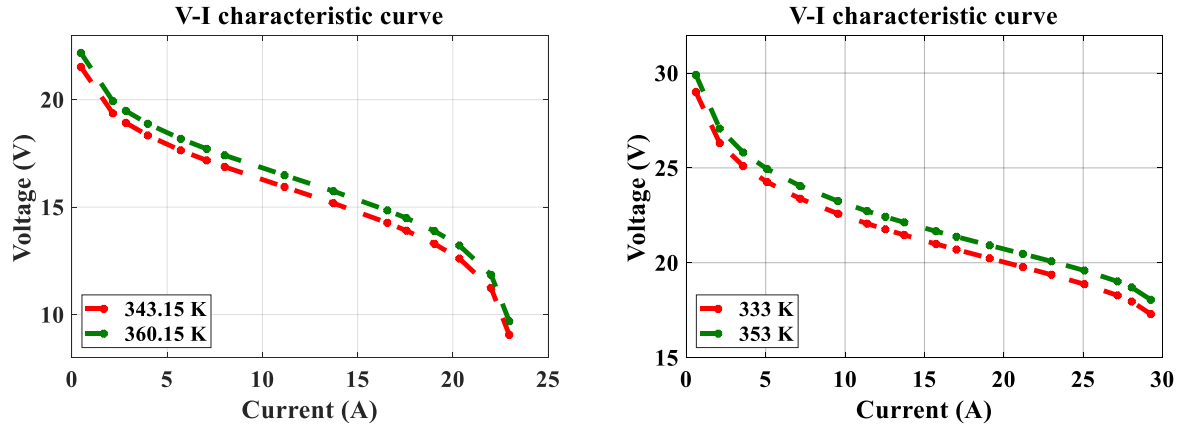
Algo	**SSE**	ε_1	ε_2 x10^{-3}	ε_3 x10^{-5}	ε_4 x10^{-4}	λ	β	R_c x10^{-4}
Mu-QIO	**1.056378**	**-1.096069**	**3.428351**	**6.117325**	**-0.954002**	**23.871431**	**0.175460**	**6.762918**
QIO	1.057119	-1.123979	3.638593	6.916723	-0.955436	23.263650	0.175880	6.499839
MMRFO[42]	1.05665	− 1.19141	3.81702	6.325072	− 0.95405	21.107816	0.175221	6.76129
MRFO[42]	1.05926	-1.04319	4.73663	6.66458	− 1.06193	14.04295	0.477393	4.74369
WOA[42]	1.06663	− 0.8532	3.3563	9.799	− 0.95400	22.3712	0.1776	6.00000

4.2 Robustness of Mu-QIO for various PMEFC stacks under diverse temperatures and pressures

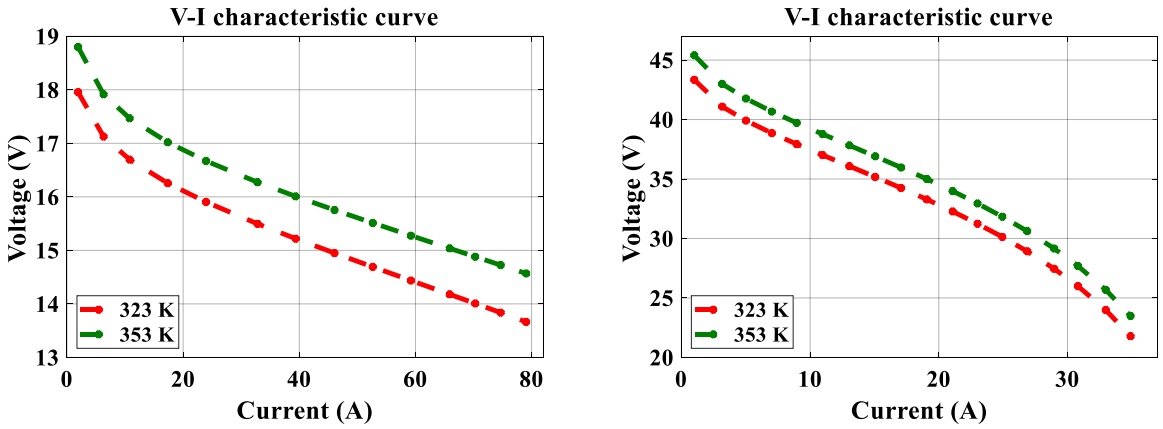
To examine the influence of temperature and pressure fluctuations on the polarization properties and validate the model's accuracy, four PEMFC stacks. The precise parameters of these stacks are consistent with those shown in Table 1, except for variations in temperature and reactant pressures across various circumstances. An analysis is first performed at various temperatures, with the reactant pressures established as detailed in Table 1 for the four PEMFC stacks. The temperature varies among the four PEMFCs. Fig.7 illustrates that when the temperature rises, the voltage output of the PEMFC stack also increases. This link may be confirmed by Eq.(3), (7), and ,(10). Eq. (3) indicates a linear correlation between temperature and the Nernst voltage, increasing the total

voltage. Concurrently, total voltage minimizes due to heightened potential drops associated with rising temperature, as delineated in Eqs 7 and 10. Nevertheless, the increase in potential drops is less pronounced than that of the Nernst voltage. Consequently, the overall voltage escalates with the increase in temperature. The temperature for both PEMFC stacks, as shown in Table 1, is considered for investigating reactant pressure change.

Fig.8 indicates that an increase in the input pressure of reactants enhances output voltage. This connection may be confirmed using Eq. (3), which demonstrates that the Nernst potential is logarithmically related to the pressure of the reactants. An elevation in reactant pressure results in an increase in Nernst voltage. Nonetheless, owing to the logarithmic form of the connection, this rise is quite low. Thus, the little elevation in Nernst voltage leads to a slight increase in the overall output voltage of the PEMFC stack. The resilience of the Mu-QIO technique in several settings demonstrates that precise polarization properties at varying temperatures and pressures can be derived from the retrieved parameters.

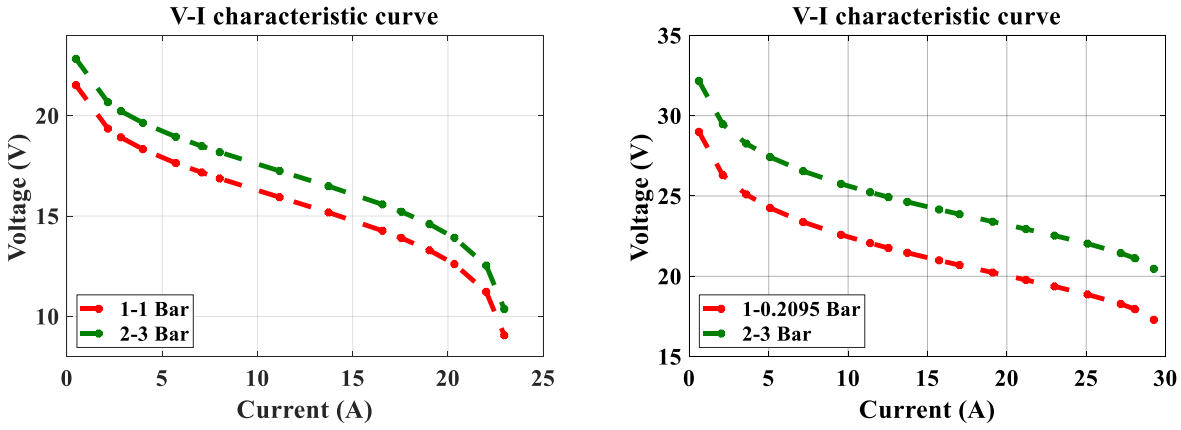


(a) (b)

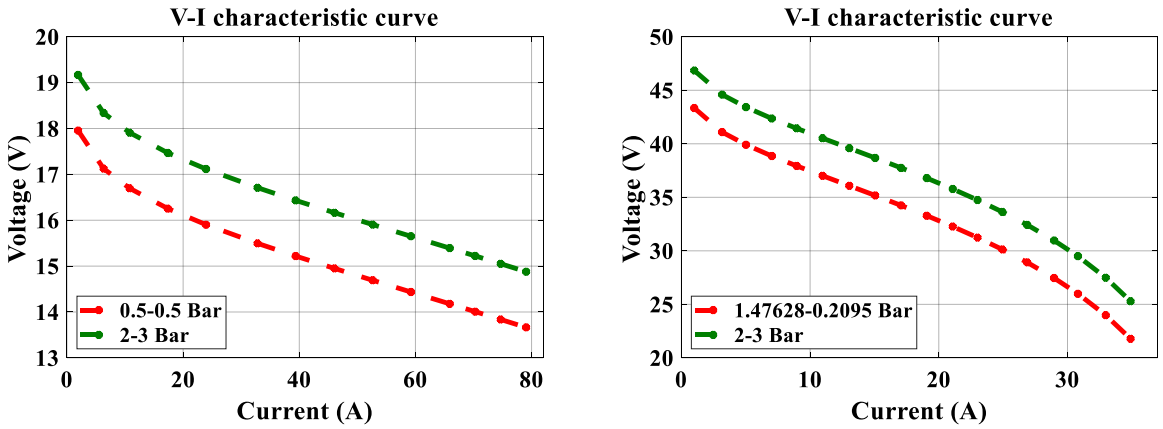


(c) (d)

Fig 7. Temperature variation for: (a) 250 W, (b) BCS-500 W, (c) Temasek 1 KW, (d) SR-12.



(a) (b)



(c) (d)

Fig 8. Pressures variation for: (a) 250 W, (b) BCS-500 W, (c) Temasek 1 KW, (d) SR-12.

4.3 Statistical analysis for various PEMFC stacks

A statistical examination of the lowest SSE values over 30 different runs is provided to confirm the robustness of the suggested Mu-QIO for parameter identification of PEMFC stacks. This research provides a precise evaluation of the suggested Mu-QIO compared to the traditional QIO.

The comparisons between the Mu-QIO and traditional QIO are conducted across numerous metrics, namely min and Worst SSE, the mean SSE, standard deviation (STD), relative error (RE), root mean square error (RMSE), mean absolute error (MAE), and efficiency. The mathematical formulations of these metrics are delineated as follows[44]:

$$SD = \sqrt{\frac{\sum_{j=1}^{30}\left(F_{oj} - F_{oj_{men}}\right)}{30-1}} \tag{27}$$

$$RE = \frac{\sum_{j=1}^{30}\left(F_{oj} - F_{oj_{min}}\right)}{F_{oj_{min}}} \tag{28}$$

$$MAE = \frac{\sum_{j=1}^{30}\left(F_{oj} - F_{oj_{min}}\right)}{30} \tag{29}$$

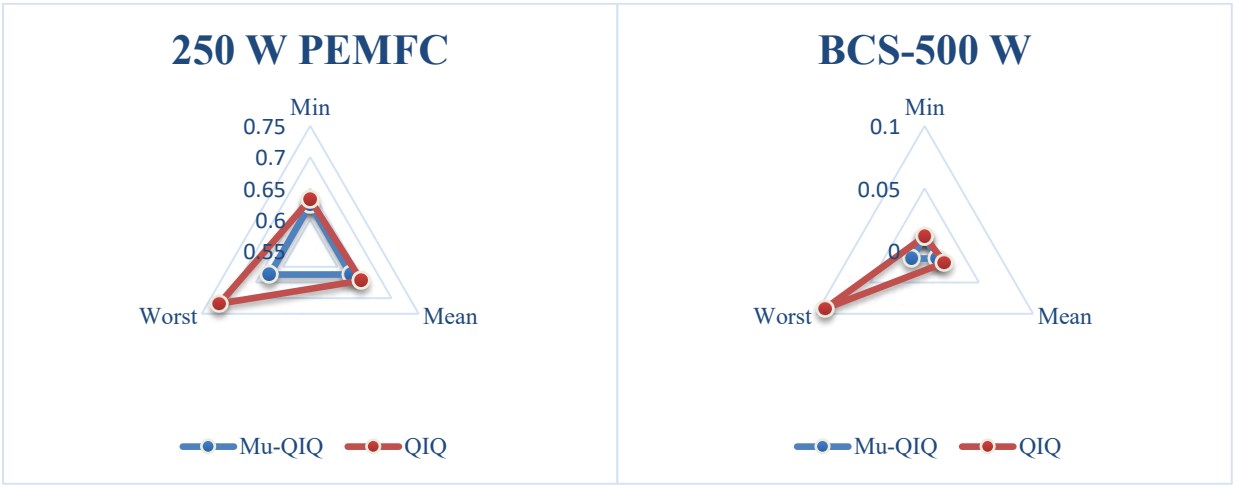
$$RMSE = \sqrt{\frac{\sum_{j=1}^{30}\left(F_{oj} - F_{oj_{min}}\right)^2}{30}} \tag{30}$$

$$eff = \frac{F_{oj_{min}}}{F_{oj}} \times 100 \tag{31}$$

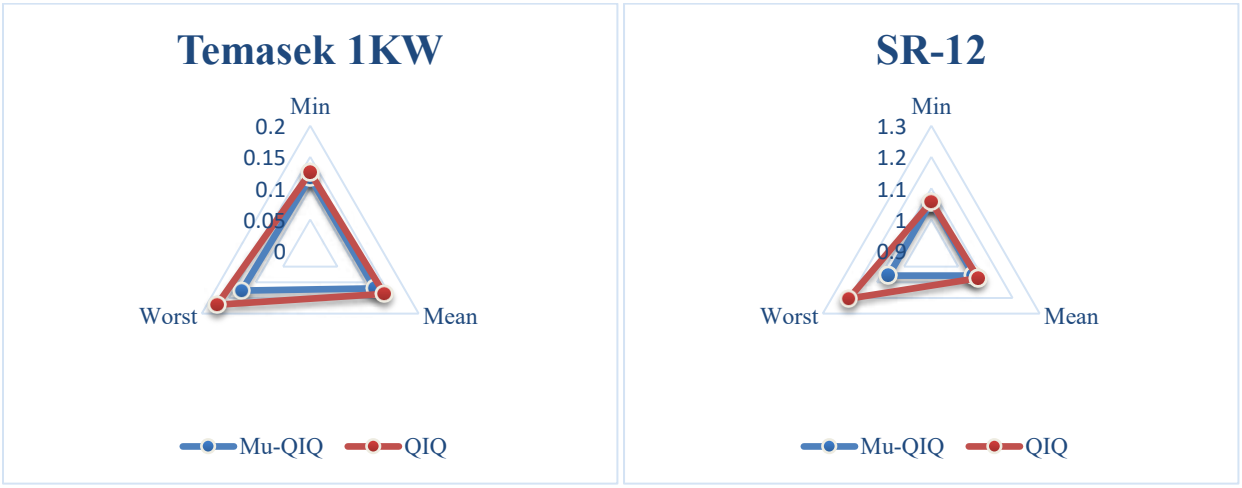
F_{oj}Represents the objective function value attained at the end of each iteration. $F_{oj_{min}}$ Denotes the total minimum best value of SSE. $F_{oj_{men}}$Denotes the average value of SSE over the 30 independent runs of the optimization procedure. The statistical outcomes of the suggested Mu-QIO algorithm and the traditional QIO are shown in Tables 7 and 8.

From these tables, the statistical analysis indicates that the suggested method outperforms all previously published algorithms and the standard QIO technique. The Mu-QIO exhibits the lowest values for maximum, minimum, average, and standard deviation of SSE when compared to the other strategies for 250 W, BCS-500 W, Temasek 1 KW, and SR-12, relative to conventional QIO and other optimization methods included in the analysis. Furthermore, the Mu-QIO surpasses the conventional QIO, achieving an efficiency of 96%. Additionally, a comparison of statistical

indices for the Mu-QIO and conventional QIO is presented in Fig. 9, demonstrating that Mu-QIO is a reliable technique. Consequently, the statistical analysis outcomes (Min, STD, RE, MAE, and RMSE) indicate the durability and reliability of the suggested Mu-QIO in accurately obtaining parameters from all commercial PEMFC stacks utilized in this study.



(a) (b)



(c) (d)

Fig. 9 Statistical indices variation for: (a) 250 W, (b) BCS-500 W, (c) Temasek 1 KW, (d) SR-12.

Table. 7 Comparative statistical analysis of the achievements of Mu-QIO with other algorithms for 250 W and BCS 500 W.

PEMFC Types	**250 W**					**BCS500 W**				
	Mu-QIO	QIO	MMRFO[42]	MRFO[42]	TGA[42]	**Mu-QIO**	QIO	P-DSO[43]	MMRFO[42]	MRFO[42]
Min	**0.624711**	0.63263	0.6420829	0.6452179	0.7496	**0.0115566**	0.011726	0.0117	0.011574	0.012951
Mean	**0.624714**	0.6440155	0.6582730	0.8610580	1.893472	**0.0116302**	0.018352	/	0.024939	0.050727
Worst	**0.624727**	0.7174741	0.7575708	0.704964	1.893472	**0.0117721**	0.091760	/	0.168013	0.212664
SD	**4.265890×10^{-06}**	0.0204420	2.58251666	4.6623546	29.77793	**7.409626×10^{-05}**	0.018352	/	3.131417	4.659308
RE	**1.577726×10^{-04}**	0.9257148	0.75645006	2.777981	18.82655	**0.1910907**	25.890562	/	34.64148	87.50345
MAE	**3.285411×10^{-06}**	0.0192776	0.01619012	0.059746	0.470417	**7.361203×10^{-05}**	0.0101198	/	0.013365	0.037776
RMSE	**5.327772×10^{-06}**	0.0278491	0.03011358	0.059746	0.554084	**1.035663×10^{-04}**	0.0206884	0.025	0.033563	0.059376
Eff (%)	**99.99947**	96.912262	97.6740098	91.881907	64.86418	**99.3631**	31.90758	/	71.99333	42.22368

Table. 8 Comparative statistical analysis of the achievements of Mu-QIO with other algorithms for Temasek 1KW and SR-12.

PEMFC Types	**Temasek 1KW**					**SR-12**				
	Mu-QIO	QIO	MMRFO[42]	MRFO[42]	SSA[42]	**Mu-QIO**	QIO	MMRFO[42]	MRFO[42]	WOA[42]
Min	**0.117106**	0.125235	0.790988	0.793815	0.796814	**1.056378**	1.057119	1.0566515	1.059258	1.0605292
Mean	**0.118953**	0.136414	0.799478	0.833819	0.8911169	**1.056491**	1.073096	1.0602985	1.121361	19.293257
Worst	**0.126374**	0.171686	0.848622	1.008512	1.0763793	**1.057292**	1.204173	1.0654995	1.361002	117.08224
SD	**3.606103×10^{-03}**	0.011443	1.421473	4.935560	8.6622815	**2.134662×10^{-04}**	0.026176	0.2630515	7.855610	2418.6350
RE	**0.473311**	3.883819	0.322029	1.511840	3.5504690	**3.227684×10^{-03}**	0.453402	0.1035436	1.758858	515.76311
MAE	**1.847587×10^{-03}**	0.015636	0.008490	0.040004	0.0943022	**1.136551×10^{-04}**	0.015976	0.0036469	0.062102	18.232728
RMSE	**3.998011×10^{-03}**	0.0192634	0.016352	0.062889	0.1270680	**2.386763×10^{-04}**	0.030292	0.0044709	0.099106	29.965190
Eff (%)	**98.96135**	87.939595	98.96709	95.49216	90.176396	**99.9892382**	98.454528	99.656634	94.86759	29.931952

5 Conclusion

A novel, efficient, and resilient hybrid Mu-QIO approach is introduced to extract the best parameters of the PEMFC model. Four distinct PEMFC stacks (250 W, BCS-500 W, Temasek 1 KW, and SR-12 proton exchange MFC stacks) are analyzed to assess the efficacy of the hybrid method in determining the undefined parameters of these fuel cell stacks and achieving precise polarization characteristics that closely match experimental data. By integrating the mutation phase of Differential Evolution with the Quadratic Interpolation Optimization (QIO) algorithm, the Mu-QIO method enhances both convergence speed and parameter estimation accuracy. Seven unidentified parameters $\varepsilon_{1,2,3,4}$ λ, β, and R_c have been ideally assessed using Mu-QIO, with the SSE serving as the goal function. The suggested method's precision was proven by the tight alignment of experimental and estimated polarization characteristics, I-V, and I-P curves. Mu-QIO correctly identifies seven unknown factors and matches measured polarization characteristics. To prove its superiority, the Mu-QIO algorithm is compared to the classic QIO method and other algorithms in the literature. Additional studies spanning temperature and pressure conditions demonstrate Mu-QIO's adaptability and robustness, while the convergence curve analysis verifies its rapid and consistent convergence. A rigorous statistical analysis shows that Mu-QIO exceeds

rival approaches in accuracy and dependability. These results demonstrate Mu-QIO's robustness and scalability in global PEMFC parameter adjustment.

Author Contributions: Conceptualization, BK.,AL, SN, AK, AA, and HR; methodology, BK.,AL, SN, and HR; software, BK.,AL, SN, and AK.; validation, BK.,AL, and SN.; formal analysis, BK.,AL, SN, AK, AA, and HR.; investigation, BK.,AL.; resources, BK.,AL,.; data curation, BK.; writing—original draft preparation, BK.,AL.; writing—review and editing, BK.,AL, SN, AK, AA, and HR.; visualization, AA, and HR

Competing Interests: "The authors declare no competing interests."

Data Availability Statement: "Data is available upon reasonable request from the corresponding author."

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