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Research paper

Finding best operational conditions of PEM fuel cell using adaptive neuro-fuzzy inference system and metaheuristics

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ABSTRACT

The optimum output power of the proton exchange membrane fuel cell (PEMFC) is dependent on operational conditions such as fuel pressure, oxidant pressure, fuel flow rate, and oxidant flow rate. Therefore, the aim of this paper is to enhance performance of PEMFC by identifying optimal operating parameters of PEMFC. The proposed strategy includes both modelling and optimization stages. An adaptive network-based fuzzy inference system (ANFIS) is utilized in creating the model based on experimental datasets. Whereas, the grey wolf optimizer (GWO) is used to identify the best values of fuel pressure, oxidant pressure, fuel flow rate, and oxidant flow rate corresponding to maximum power PEMFC. The obtained results demonstrated the superiority of the integration between ANIFS based modelling and GWO. Regarding the modelling accuracy, The RMSE values are 0.017 as well as 0.0262 respectively for treating and testing phases. The coefficient of determination values is 0.9921 as well as 0.9622 respectively for treating coupled with testing phases. The optimal parameters are 1.0 bar, 0.8 bar, 117.03 mL/min, 150.0 mL/min respectively fuel pressure, oxidant pressure, fuel flow rate, and oxidant flow rate corresponding to maximum power of PEMFC. Thanks to the integration between ANFIS-based modelling and GWO, the output power of PEMFC has been increased from 0.587 W using experimental work to 0.92 W.

1. Introduction

As the world advance towards green energy technology, one of the pragmatic approaches that could be adopted to make this a reality is its medium of harnessing energy from sustainable sources (Baroutaji et al., 2019; Barnoon et al., 2021, 2022). Even though fossil commodities remain dominant in the energy generation industry, issues pertaining to their sustainability coupled with their harmful effect on the environment has been the bane for the clarion call by the research community for the world to explore other energy generating sources (Nguyen and Fushinobu, 2020). Most scientific research papers consider renewable energy as suitable option for the highly dependent fossil product especially in the energy sector. Fuel cell, an energy converting device and a type of renewable source of energy is gradually making headlines in the energy sector because of the reactants used during its energy generation process (Ijaodola et al., 2019; Barnoon, 2021; Chen et al., 2021a). It is basically an electrochemical device that produces energy in the presence of an oxidant and a fuel. Producing electrical energy using fuel cell comes with zero toxic substances being released into the atmosphere. Similarly, the absence of movable parts in fuel cells equally make them suitable for several applications as the issues of wear, friction, tear etc is curbed (Sayed et al., 2019). In terms of maintenance, the absence of movable parts implies less cost and time need in replacing specific components unlike other sources of harnessing energy. These coupled with the high efficiency of fuel cells are underpinning factors accelerating the commercialization of these sources of energy generation. The efficiency of fuel cell is dependent on operational conditions around the cell, and this has a ripple effect on the efficiency of the cell (Chen et al., 2021b). It is hence imperative that a suitable approach for the validation of these cell operating conditions is explored either via the utilization of numerical models, experimental methods, or both (Marefati and Mehrpooya, 2019; Rezk et al., 2022). Using the numerical methods, specific cell parameters like the heat transfer, fluid flow etc can easily be investigated.

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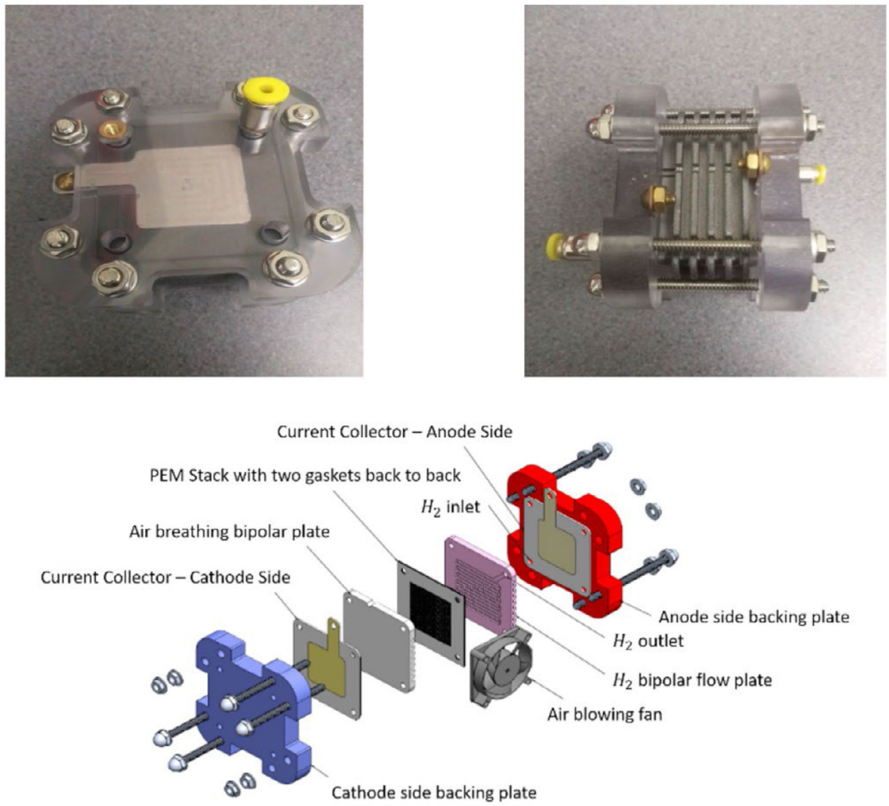


Fig. 1. Pictorial representation for PEMFC (Olabi et al., 2021).

Table 1
Parameters considered for the experimental investigation.

Design condition	−1	0	0
Input variable	1st	2nd	3rd
Pressure of hydrogen (bar)	1	1.75	2.5
Pressure of Oxygen	0.8	1.55	2.3
Hydrogen flow rate (mL/min)	15	82.5	150
Oxygen flow rate (mL/min)	15	82.5	150

One of the common types of fuel cell useful for several applications due to its lower operational temperature is the PEMFC. As depicted in Fig. 1, PEM fuel cells comprise of membrane electrode assembly which serves as the platform for the reaction of the hydrogen fuel and the oxidant. To accelerate the chemical reaction process, platinum is utilized but this has a negative effect on the overall cost of the unit because of the platinum being very expensive (Olabi et al., 2021). Other justification for appreciable increase in terms of the sale of PEM fuel cell units include its quick response. The fuel type that can be adopted in the smooth running of the cell is enormous.

PEM fuel cells though highly recommended for the automotive industry, they are also suitable in producing power (Omran et al., 2021). Solid oxide fuel cell are functions best at elevated temperature, but this makes the entire process more expensive compared to PEM fuel cells (Ogungbemi et al., 2019). With more research activities being championed in terms of the safety of hydrogen production, refuelling as well as an appreciable increase in energy density, the future of these energy generation units is remarkable. Other research activities are being carried on various components in the cell with primary focus on improving the overall performance of the cell (Chen et al., 2019; Rezk et al., 2019; Chen et al., 2022a). Notable among these parts includes the MEA, bipolar plate etc. In terms of current density, the last decades has also seen the current density of fuel cells being increased appreciably as well and this is directly correlated to the cell's life span (Huang et al., 2021). Again, other academics are also exploring ways for recovering the components in PEMFC once their usefulness has been exhausted (Bicer et al., 2016; Mohanta et al., 2019; Chen et al., 2022b; Valente et al., 2019). Failure modes coupled with material degradation have also seen significant investigation, but the reality is all these investigations are geared towards enhancing the cell performance and most of them are carried out under varying cell conditions (Khatib et al., 2019). It is therefore important that a holistic study into key factors impacting the performance of the cell is critically evaluated (Ogungbemi et al., 2021). The efficiency is also directly proportional to the design and control of the system but that is equally dependent on a proper comprehension of the internal characteristics of the cell i.e the input as well as output of the fuel cell. Most experimental work carried out in the past were often dependent on analysis of the thermodynamics as well electrochemical activity of the cell but today all these tasks can be performed numerically (Mei et al., 2022). In performing this activity, key primary information on various parts of the cell must be clearly defined but some of these technical details are often know to only the manufacturers hence to a large extent the absence of some detailed information implies that the model cannot be utilized. All these technical issues form the basis on the need for a forensic study into the optimization of various cell operating conditions that would enhance cell efficiency.

The purpose of the current research paper is to improve output power of PEMFC by determining optimal values of fuel pressure,

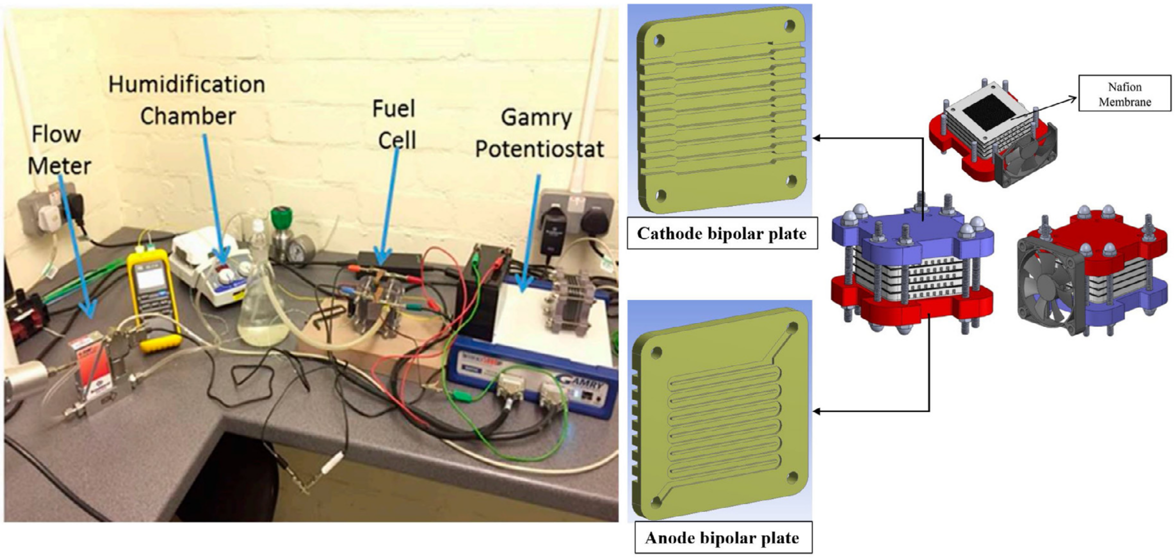


Fig. 2. Experimental set up.

Table 2
Material composition for various cell components considered for the investigation.

Composition of cell	Material	Features
Covering	Acetyl	Obtained from fuel cell store with membrane surface area of 11.56 cm^2
Membrane	Nafion 212	Catalyst loading 0.4 mg/cm^2 Pt/c.0.55 g cm^3 bulk Supplier: Fuel cell store; 24 pores/cm
Anode flow plate	Graphite	Thickness: 0.65 mm Supplier: Fuel Cell Store
Sealing	Silicon	Thickness: 0.8 mm Supplier: Fuel Cell Store

Table 3
Statistical evaluations of the ANFIS-based model.

MSE			RMSE			Coefficient of determination (R^2)		
Train	Test	All	Train	Test	All	Train	Test	All
2.8824e−04	0.0007	0.0004	0.017	0.0262	0.0204	0.9921	0.9622	0.9865

Table 4
Optimal parameters using experimental and proposed strategy.

Strategy	Hydrogen pressure	Oxygen pressure	Hydrogen flow rate	Oxygen flow rate	Power (W)	Improvement (%)
Experimental	1.0	0.8	82.5	82.5	0.587622	0.0
Proposed strategy	1.0	0.8	117	150	0.9216	56.73

oxidant pressure, fuel flow rate, and oxidant flow rate. Proposed strategy includes both modelling and optimization stages. An adaptive network-based fuzzy inference system (ANFIS) is utilized to create model based on experimental datasets. Whereas, the grey wolf optimizer (GWO) is used to identify the best values of fuel pressure, oxidant pressure, fuel flow rate, and oxidant flow rate corresponding to maximum power PEMFC. The main contributions in this paper are outlined as follows:

- ANFIS model has been developed subject to experimental results to model PEMFC based on fuel pressure, oxidant pressure, fuel flow rate, and oxidant flow rate.
- A new application of the grey wolf optimizer is proposed to identify best parameters of fuel pressure, oxidant pressure, fuel flow rate, and oxidant flow rate that maximize output of PEMFC.
- The suppository and robustness of the proposed strategy has been proved
- The maximization output of PEMFC is confirmed using proposed strategy

The remainder of the work is prepared according to the following detailed sections; Section **2** introduces experimental work. ANFIS-based modelling and grey wolf optimizer have been described in detail in Section **3**. The results and discussions are presented in

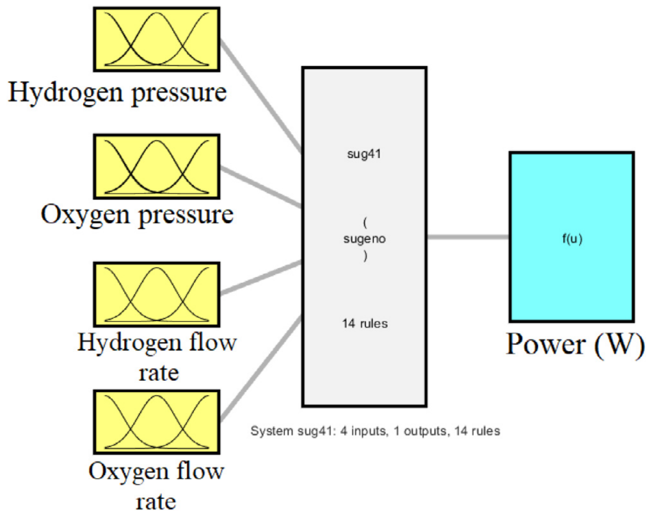


Fig. 3. ANFIS-based model configuration.

Section **4**. Lastly, Section **5** presents a summary of the outcome of the investigation.

2. Experimental work

2.1. Fuel cell testing

The cell used for this investigation was acquired from fuel cell store. With active area of 11.46 cm ^{2}, the cell was properly humidified in tandem to recommendation of the manufacturer. This was carried out to prevent the membrane from drying up as this often results in an increase in ohmic losses which will eventually reduce the overall cell performance. Using varying operating conditions as captured in Table 1, the performance of the cell was evaluated. Optimization of the various operational conditions were performed mainly to ascertain the best condition that would yield maximum power density output. Air pressure was initially considered at values lower than hydrogen pressure.

2.2. Experimental set up

The experimental setup considered for this study is captured in Fig. 2. Using hydrogen generator from Peak Scientific, UK, clean hydrogen with purity of 99.999% was channelled to the fuel cell via a flow metre. This allowed the flow rate of the hydrogen gas to be properly determined before proceeding to the cell. The oxidant for the investigation was obtained using a fan. The fuel pressure was varied between 1–2.5 bar. To keep the membrane well humidified, the fuel was passed through a humidification chamber before flowing to the anodic electrode of the cell. The electrochemical characteristics of the cell was deduced with the aid of potentiostat specifically from Gamry instruments. The voltage as well as current was also determined using a multimeter. Cell operating temperature under varying conditions was also deduced using a thermocouple. Material characteristics for the fuel cell components are captured in Table 2.

2.3. Measured response

Voltage was one of the primary responses considered in this investigation. From ohm's law, there is a direct correlation between voltage and current, but this is subject to the resistance encountered in the circuit as depicted in Eq. (1).

$$V = I \times R \tag{1}$$

The potential difference is denoted as V whiles the resistance in the cell is R and current is I.

In fuel cells, the energy harnessed from the cell electrically coupled with the voltage is deduced on the cell is running under thermodynamically reversible conditions. The net output voltage from the cell is obtained via the subtraction of irreversible potential (V_{irrev}) from reversible potential ($V_{\text{rev}} = E_{\text{r}}$) as depicted in Eq. (2). The activation polarization, ohmic losses and mass concentration losses are denoted as v_{act}, v_{ohmic}, v_{conc} respectively.

$$V(i) = V_{\text{rev}} - V_{\text{irrev}} \tag{2}$$

$$V_{\text{irrev}} = v_{\text{act}} + v_{\text{ohmic}} + v_{\text{conc}} \tag{3}$$

The output cell voltage is therefore summarized in Fig. 4
$V(\text{i}) = E_{\text{r}} - (v_{\text{act}} + v_{\text{ohmic}} + v_{\text{conc}})$

The cell voltage and current were obtained from the experimental procedure explained earlier. The cell generates currents whenever reactants are adequately supplied to the cell. Electrical efficiency of the cell is harnessed from the open circuit voltage. For instances where the open circuit voltage is low, the electrical efficiency is also likely to be low. The power density which remains one of the keys outputs from this investigation is basically a product of the current and voltage taking into account the active area of the cell.

3. Proposed methodology

In the current research work, the proposed methodology contains two phases: ANFIS-based modelling and optimization

3.1. ANFIS-modelling

Roughly in the early 90th of the last century, Jang suggested the ANFIS (Jang, 1993). ANFIS integrates the two approaches of artificial neural network (ANN) and fuzzy logic (FL). The fuzzy modelling method is characterized by a networking arrangement, which simulates the FIS as an ANN. The FIS is comprised of 3 major stages: the fuzzification, the inference system and the defuzzification. The fuzzifier and defuzzifier are two inversely operations. The former converts the crisp input values to their fuzzy values however the latter carry out the inverse process. The fuzzification and the defuzzification are accomplished with the help of the membership function (MF). ANFIS typically uses the Sugeno form fuzzy rule as it is simpler to formulate the mathematical implementation of the procedure. An example Sugeno-type rule form of three-input single-output system is presented in the following statement:

IF I_1 is A_1 and I_2 is A_2 and I_3 is A_3 THEN O = $f(I_1, I_2, I_3)$
where, I_1, I_2, I_3 denote the system inputs; A_1, A_2, A_3 are the MF shapes; O is the system output which is a function of the system inputs.

3.2. Grey wolf optimizer

GWO is one of the stochastic optimizers. It simulates the natural hunting mechanism of grey wolves by taking into consideration a leadership hierarchy. In optimization process of GWO, the solutions (wolves) are grouped, corresponding to their ranks, to four types: alpha, beta, gamma, and omega. Alpha is the high ranking where omega is the smallest. The updating principle of the proposed solution (wolf) at iteration t, x, will be as follows:

$$x(t+1) = \frac{x_1 + x_2 + x_3}{3} \tag{4}$$

$$x_1 = x_\alpha - A_1.D_\alpha, x_2 = x_\beta - A_2.D_\beta, x_3 = x_\gamma - A_3.D_\gamma \tag{5}$$

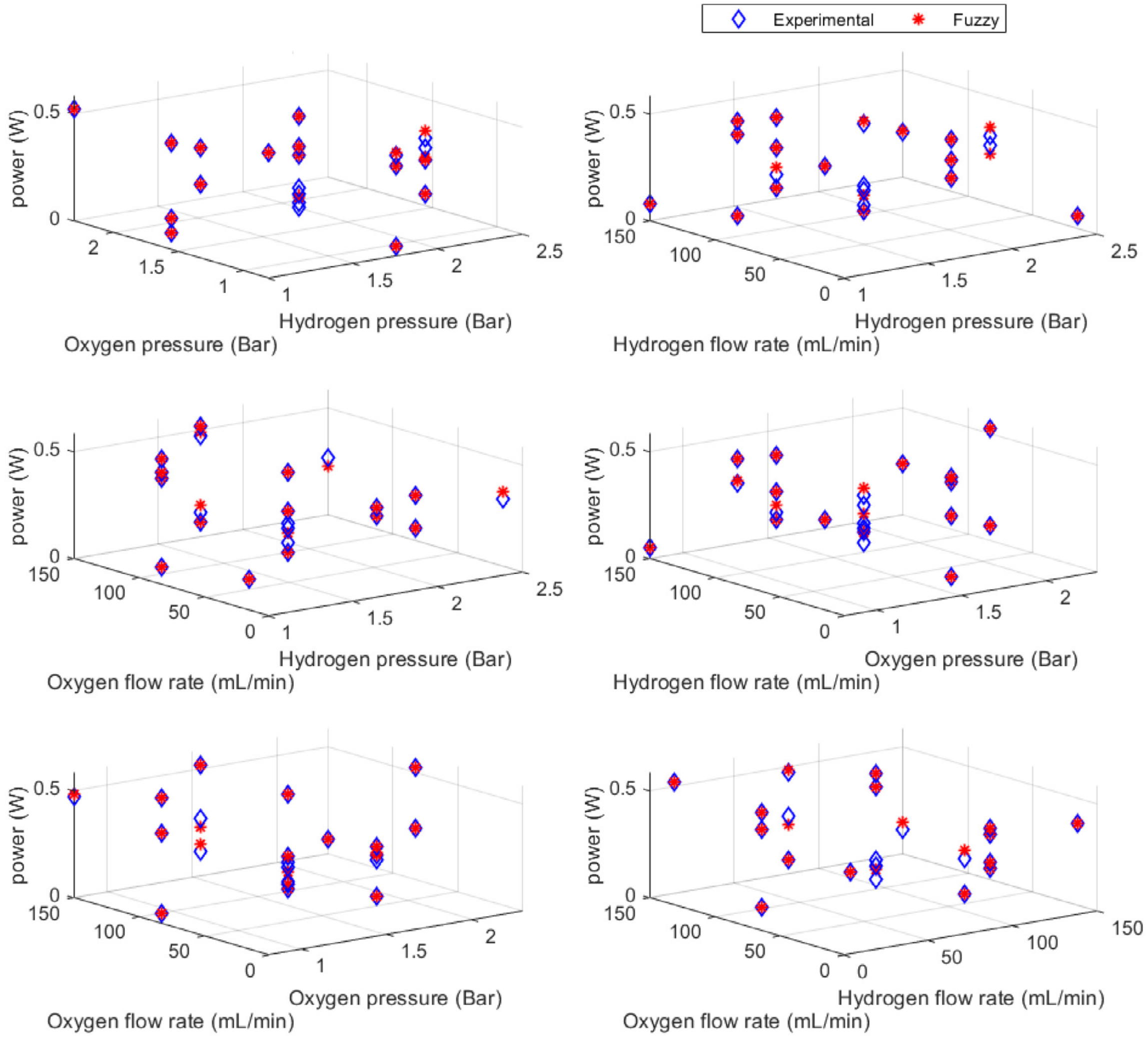


Fig. 4. 3-D spatial shape that relates the input controlling parameters.

$$D_{\alpha} = |c_1 r.x_{\alpha} - x(t)|\,, D_{\beta} = \left|c_2 r.x_{\beta} - x(t)\right|,$$
$$D_{\gamma} = \left|c_3 r.x_{\gamma} - x(t)\right|, \tag{6}$$

where, x is the wolf's position; A_1, A_2 and A_3 are random values in the interval [-2a, 2a] and a is decreased from 2 to 0 throughout the iterations; x_{α}, x_{β} and $x_{\gamma}$are the position of wolves in the alpha, beta and gamma types, respectively; c_1, c_2 and c_3 are random numbers in the range [0 2]; r is a random generator in the range [0 1].

More details about the GWO can be found in Mirjalili et al. (2014).

4. Results and discussion

4.1. ANFIS based results

In the current research paper, the MF type, the fuzzy rules generator and the defuzzification process are Gaussian-shape, the Subtractive Clustering (SC) and the Weighted Average (WAvg) respectively. The experimental data is comprised of 22 points that were divided into two groups. The first group contains 15 points for training phase whereas as the second one contains 7 points for testing phase. The ANFIS is trained with a hybrid method by using LSE in the forward path and the Backpropagation in the backward path. The SC is used to produce the system's rules which were in this case study 14 rules. Then, the model was trained until a lower MSE was achieved. The statistical evaluation of the ANFIS-based model is displayed in Table 3. Fig. 3 presents the ANFIS-based model structure. It consists of four inputs (fuel pressure, oxidant pressure, fuel flow rate, as well as oxidant flow rate) and one output (power). Considering Table 3, the RMSE values are 0.017 as well as 0.0262 respectively for training coupled with testing. The coefficient of determination values are 0.9921 as well as 0.9622 respectively for training and testing. This proves dominance of ANFIS modelling.

Figs. 4–6 show 3-D spatial shape that relates the input controlling parameters, the 3D surface, and the input membership function (MF) shapes of ANFIS-based model, respectively. Indeed, the mapping of the 3D surface with contours supports in examining the relation between the inputs and the output properly. The input MFs provides data distribution of the inputs and its influence on the output. From Fig. 5, it can be noticed that the contour colours define the effective range of the three controlling variables fuel pressure, oxidant pressure, fuel flow rate, and oxidant flow rate as [1 2.5], [0.8 2.3], [15 150] and [15 150], respectively. Within the effective range, the output power of PEMFC reaches its maximum value. The red colour contour denotes the area with higher output while the blue colour contours define the area of smaller output.

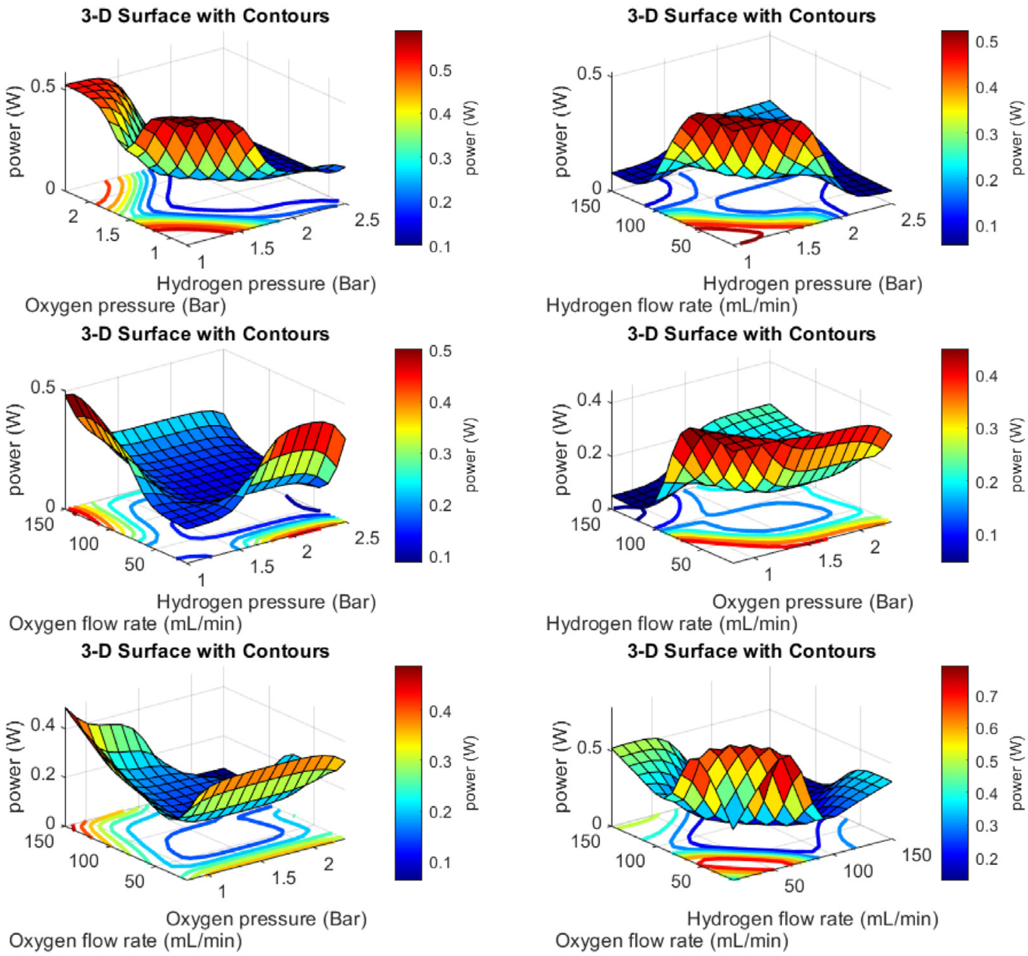


Fig. 5. Three-dimension surface for The ANFIS model.

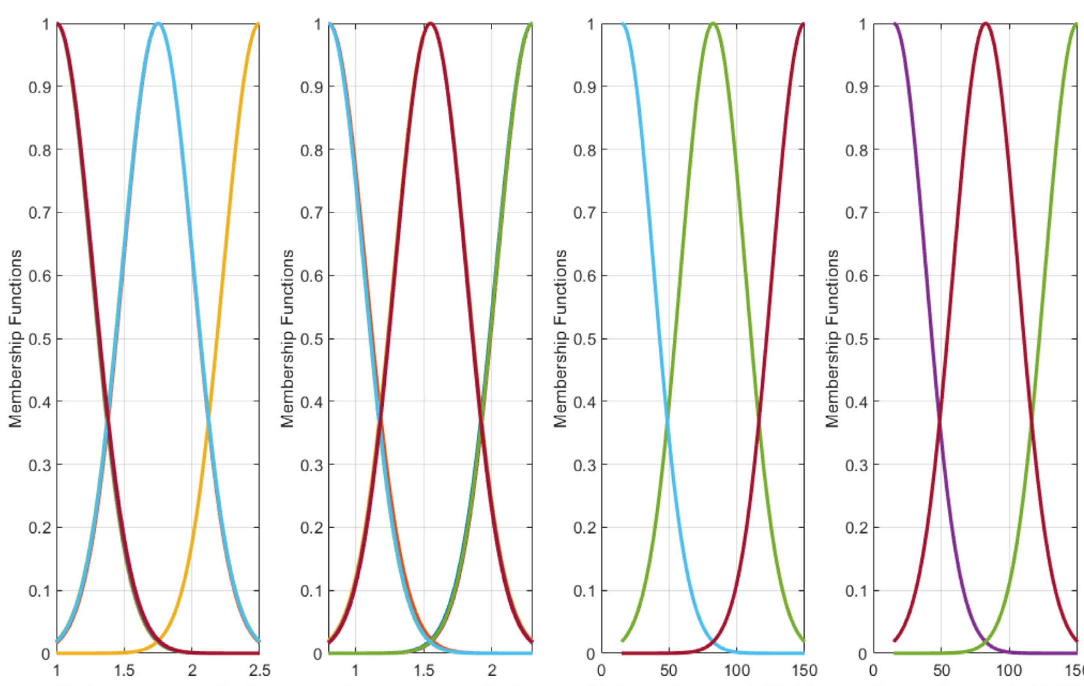
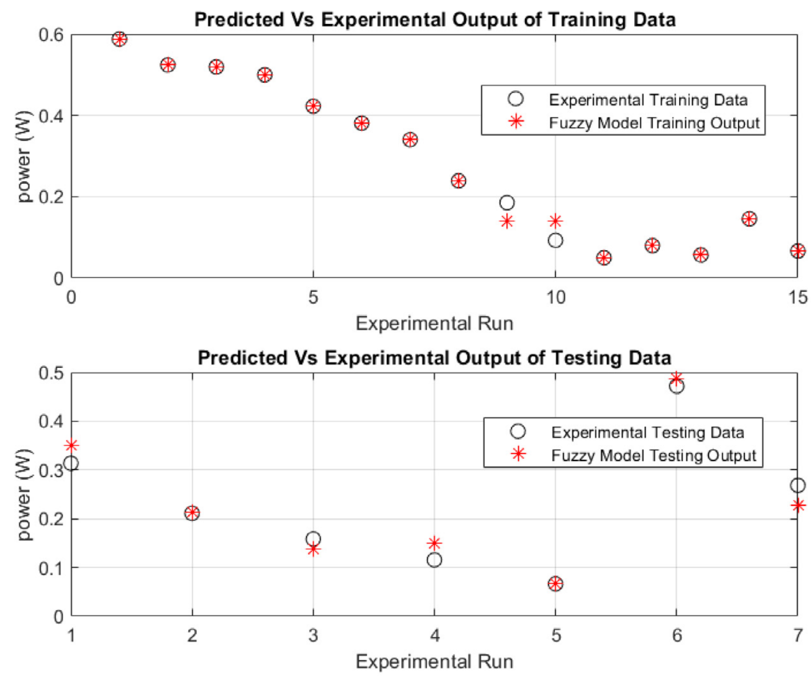
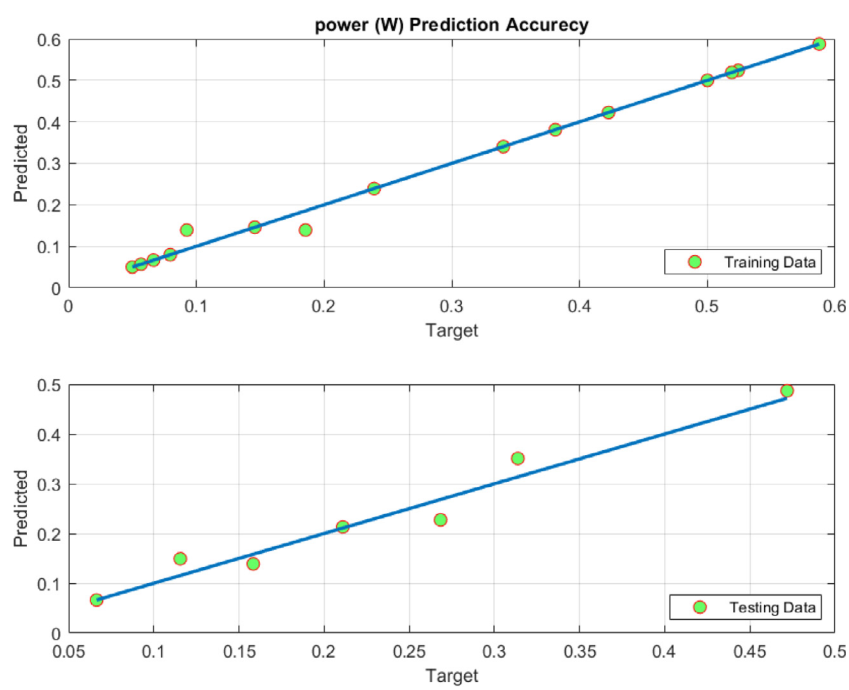


Fig. 6. Hydrogen fuzzy model inputs' MFs.



(a)



(b)

Fig. 7. ANFIS-based model prediction accuracy.

The well-matching plots of the training and testing data points demonstrate the consistent modelling stage where the model predictions are approximately the same as the experimental data not only for the training set but also for the testing set as presented in Fig. 7. This indicates that the ANFIS-based model passed the training and testing phases effectively.

4.2. Optimization based results

The objective of this work is to identify the optimal set of values of the input variables that produce the maximum power from PEMFC. Consequently, after building a consistent ANFIS-based model, grey wolf optimizer has been utilized to evaluate

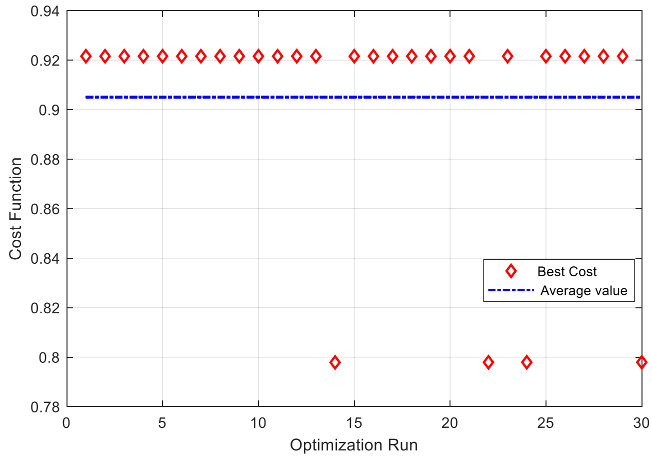


Fig. 8. Cost function evaluation through 30 runs using GWO.

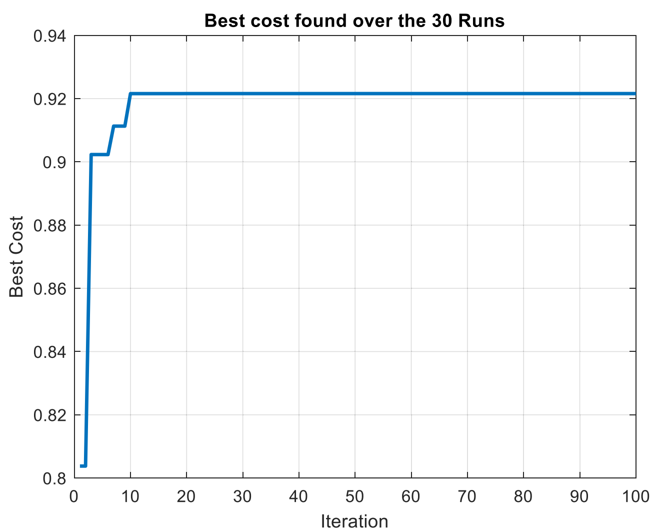


Fig. 9. Best cost function variation during the optimization process.

the best solution. Problem statement of the current optimization process can be formulated as:

$$x = \arg\max_{x \in R}(y) \tag{7}$$

where, x is the set of input variables and y is the output variable.

In this work, the input variables are fuel pressure, oxidant pressure, fuel flow rate, and oxidant flow rate while the output is the output power of PEMFC. The considered optimizer is a meta-heuristic class, i.e., it is look for the optimal solution based on a stochastic search. Therefore, the optimization process must be executed several times to accept its results and to avoid obtaining the solution by randomness. Consequently, the optimization process was executed 30 times (runs). The resulting outputs of this operation are plotted in Fig. 8. Fig. 9 shows best cost function variation during the optimization process.

To have a clear vision on the changing mechanism of the solutions throughout the optimization process, the plot of the variations of the inputs for the GWO are demonstrated in Fig. 10. The figure illustrates the distribution of the proposed 30 solutions at the beginning of the 100-iteration optimization process and then they converge to the optimal solution at the end of the iterations. As presented in Table 4, the optimal parameters using experimental and proposed strategy. From the table, the optimal parameters are 1.0 bar, 0.8 bar, 117.03 mL/min, 150.0 mL/min respectively fuel pressure, oxidant pressure, fuel flow rate, and oxidant flow rate corresponding to maximum power of PEMFC. Thanks to the integration between ANFIS-based modelling and GWO, the output power of PEMFC has been increased from 0.587 W using experimental work to 0.92 W. It is increased by 56.73% in comparison with the experimental work.

5. Conclusion

Four input parameters namely fuel pressure, oxidant pressure, fuel flow rate, and oxidant flow rate are mainly influence on the output power of PEMFC. Consequently, goal of this work is to determine the best input operating parameters that maximize the output power of PEMFC. The suggested approach involves two phases: modelling and optimization. First and foremost, using experimental data, An ANFIS-based model was developed with high accuracy. The RMSE values are 0.017 and 0.0262 respectively for treating as well as testing phases. The coefficient of determination values is 0.9921 and 0.9622 respectively for treating and testing phases. Secondly, a grey wolf optimizer (GWO) has been implemented to determine the best solution. During the optimization process the fuel pressure, oxidant pressure, fuel flow rate, and oxidant flow rate are utilized as decision variables whereas as the output power of PEMFC is assigned to be the objective function that needed to be a maximum. The obtained optimal parameters were 1.0 bar, 0.8 bar, 117.03 mL/min, 150.0 mL/min respectively fuel pressure, oxidant pressure, fuel flow rate, and oxidant flow rate. Under this condition the corresponding maximum power of PEMFC is 0.92 W. It is increased by 56.73% in comparison with the experimental work. Finally, the superiority of the integration between ANIFS-based modelling and GWO has been proved.

CRediT authorship contribution statement

Hegazy Rezk: Methodology, Software, Conceptualization, Formal analysis, Writing – review & editing. **Tabbi Wilberforce:** Experimental, Formal analysis, Writing – review & editing. **Enas Taha Sayed:** Software, Formal analysis, Writing – review & editing. **Ahmed N.M. Alahmadi:** Supervision, Formal analysis, Writing – review & editing. **A.G. Olabi:** Supervision, Formal analysis, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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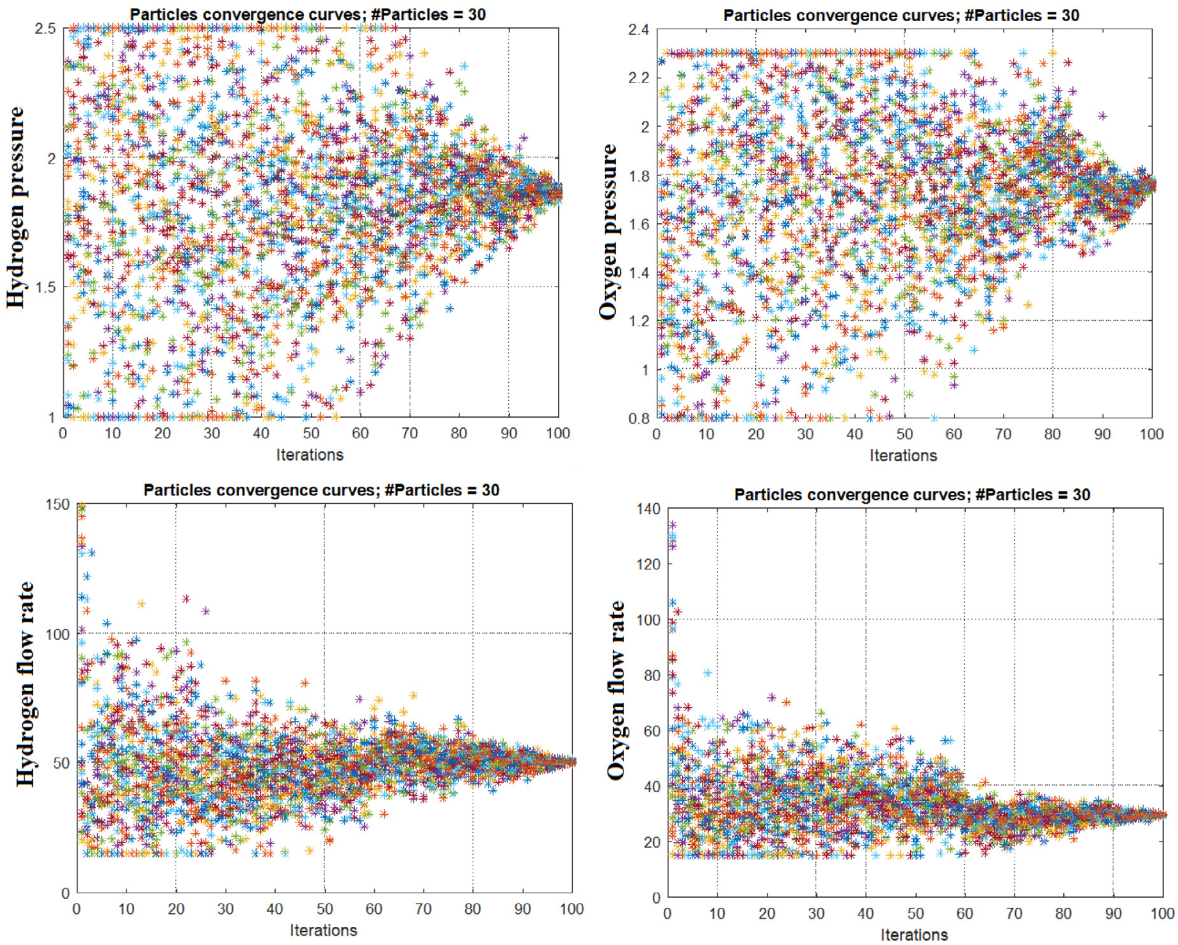

Fig. 10. Decision variables variation during the optimization process.

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