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Implementation of Adaptive Neuro-Fuzzy Inference System (Anfis) for Performance Prediction of Fuel Cell Parameters

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ABSTRACT

Fuel cells are potential candidates for storing energy in many applications; however, their implementation is limited due to poor efficiency and high initial and operating costs. The purpose of this research is to find the most influential fuel cell parameters by applying the adaptive neuro-fuzzy inference system (ANFIS). The ANFIS method is implemented to select highly influential parameters for proton exchange membrane (PEM) element of fuel cells. Seven effective input parameters are considered including four parameters of semi-empirical coefficients, parametric coefficient, equivalent contact resistance, and adjustable parameter. Parameters with higher influence are then identified. An optimal combination of the influential parameters is presented and discussed. The ANFIS models used for predicting the most influential parameters in the performance of fuel cells were performed by the well-known statistical indicators of the root-mean-squared error (RMSE) and coefficient of determination (R^2). Conventional error statistical indicators, RMSE, r, and R^2, were calculated. Values of R^2 were calculated as of 1.000, 0.9769, and 0.9652 for three different scenarios, respectively. R^2 values showed that the ANFIS could be properly used for yield prediction in this study.

1. INTRODUCTION

1.1. Motivation

Fossil fuels are the most common energy resources in the world. This study chose to investigate clean and renewable energy sources for reasons such as fossil fuel depletion and environmental pollution [1]. Hydrogen is an abundant source of renewable energy in the world, which can be utilized by fuel cells [2]. Air pollution, climate change, and numerous environmental hazards are the prime examples of the consequence of the world's excessive dependence on fossil fuels [3]. The tendency for using different renewable energies is extremely important because of many advantages such as lower price, availability, environmentally friendliness, and most importantly, sustainable economic development [4]. Wind is another source of clean energy, which is clean and abundant in many parts of the world. However, it is not continuously available [5]. Geothermal is also another source of energy, which is continuously available without interruption. It can be used to produce clean hydrogen, too [6]. Photovoltaics is currently being used for numerous purposes like hydrogen production [7]. Solar energy is also another source of clean energy, which has recently been used in many countries [8]. There have been different researches related to implementing renewable energies, especially hybrid [9-12].

One of the most common fuel cell applications is seen in the transport sector due to its advantages. Among different types of fuel cells, Proton Exchange Membrane ones are of great value that have been viable in stationary and portable applications [13, 14]. They benefit from lower temperature/pressure ranging between 50 and 100 degrees, and it is a suitable replacement for alkaline types. This type is made of electrodes, electrolytes, catalysts, and gas diffusion layers whose whole system turns the chemical energy generated during the reaction of hydrogen and oxygen into electricity [15].

In the process of fuel cells, oxygen reacts with hydrogen to generate water [16]. Fuel cells have several advantages that include generating electricity with minimum pollution [17].

Designing the parameter for the multi-objective PEM fuel cell stack was performed by a hybrid adaptive neuro-fuzzy inference system and genetic algorithms [18]. To reveal the actual performance of proton exchange membrane fuel cell (PEMFC) and to enhance the performance of the system and planning the fuel cell power conditioning circuits, it is vital to develop a suitable model for the performance of fuel cells [19]. The mathematical modeling will facilitate better designing and testing of fuel cells and help understand the occurrence of potential events [20].

Since the parameters of the model are related to fuel cell operating conditions, predicting its characteristics is one of the most difficult issues in modeling fuel cell systems [21]. The parameter estimation of PEMFC systems is a major problem in modeling these systems and makes the PEMFC system complex. Priya et al. [13] provided the basis for the present mathematical modeling used in this research.

1.2. Literature survey

Boas et al. [22] studied the effect of configuration parameters such as anode electrode size, area of membrane, design of

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cell, and operation conditions. They used synthetic wastewater for a dairy manufacturing effluent to show the effects of configuration parameters. They also showed that different configuration and operation conditions were influenced by energy production and characteristics of biofilm. Karpenko-Jereb et al. [23] investigated the effect of transformations in the quantity of the catalyst layers, layer of gas diffusion characteristics, and polymer electrolyte membrane on the capability of a PEMFC. They also compared the obtained values with the outputs of a referenced example. Finally, they showed that thickness and conductivity variations of the PEM and GDL had led to substantial changes in fuel cell performance. Chavan and Talange [24] proposed a model to evaluate the PEM performance of fuel cells under different operational conditions and, then, compared the model with other models. Finally, results showed that the proposed model was more simple and realistic than the former ones. In another research, Chavan and Talange [25], for the first time, applied the black-box system identification approach for developing a number of simple, yet real, models to predict the PEM performance of fuel cells. Li et al. [26] investigated the performance prediction of fuel cells by using a developed model considering the relationships between agglomerate parameters. Wu et al. [27] scrutinized the effect of operational parameters on the performance of PEM fuel cells. El-Fergany [28] utilized a technique, called Salp Swarm Optimizer (SSO), for defining the best values of parameters, which are unknown. In another study done by Fathy and Rezk [29], an algorithm called multi-verse optimizer was implemented for identifying parameters, which are optimal.

Mitov et al. [30] evaluated electrical parameters related to nine different freshwater sediment microbial fuel cells (SMFCs) for 20 months. The examination of data indicated that all SMFCs reached steady conditions after an operation period of 300 days. The obtained values of the electrical parameters showed that the performance of SMFCs enjoyed great reproducibility and repeatability. Rajaskar et al. [31] presented a new model for maximizing power with focus on fuel cell parameter extraction. The proposed model was implemented by the simple genetic algorithm (GA). They indicated that the proposed model converged to optimum extracting fuel cell parameters in a reasonable computational time. Priya et al. [13] proposed a mathematical model to estimate fuel cell parameters. They applied the GA to solve the proposed model.

Artificial neural networks (ANN) were used for the analysis method, because it did not need knowledge of internal system parameters. ANFIS is popular for selecting the most influential parameters of fuel cells outputs [32-34]. Verma and Pitchumani [35] investigated the ANFIS of prediction capabilities. They showed that it was an efficient method for dealing with uncertainties in their systems [35]. ANFIS was used as a powerful hybrid tool by many researchers in different engineering systems.

There are several research studies related to the application of ANFIS to estimate and control the behavior of engineering systems. Singh et al. [36] applied the neuro-fuzzy system to forecast Young's modulus of rock to overcome ANN limitations. Mostafaei [37] applied the ANFIS model to predict the cetane number of biodiesel fuels by implementing the desirability function. Vakhshouri and Nejadi [38] applied the ANFIS for predicting compressive strength in the case of self-compacting concrete. Kurnaz et al. [39] proposed an ANFIS method to control the location of the unmanned aerial vehicles (UAVs) in 3D space by considering three fuzzy logic modules. Yang et al. [40] investigated ANFIS and NN, improved by DE algorithm. Tian and Collins [41] applied an ANFIS method to control a flexible manipulator composed of two recurrent neural networks in the forward path and a fuzzy logic controller in the feedback control. Ekici and Aksoy [42] proposed an ANFIS method to predict the consumption of building energy in cold regions. Khajeh et al. [43] illustrated the effectiveness of ANFIS to forecast the solubility of carbon dioxide in polymers. Inal [44] evaluated the dielectric attributes of polyesters by an ANFIS model in a wide and different range of conditions. Lo and Lin [45] applied the ANFIS to forecast non-uniformity on surface in chemical mechanical polishing (CMP) processes.

1.3. Novelty

Many researchers have used the ANFIS for enhancing the capability of automatic learning and adaptation [35-39]. There have also been many other research studies that applied ANFIS for estimating and identifying different systems in real-time mode [40-45]. According to the subject literature, Parya et al. [13] estimated the parameters of the mathematical model of PEM fuel cell by the genetic algorithm method. In the present work, the ANFIS method was used to determine the parameters on which the fuel cell performance depends dominantly and predict the fuel cell behavior. The results of this method showed to be superior to the genetic algorithm in terms of efficiency and optimality. In fact, there are weaknesses in the genetic algorithm that can be covered by better methods such as the ANFIS method. Therefore, the ANFIS method is a better technique to estimate the parameters of a PEM fuel cell for the following reasons:

1- If the search space is relatively small, the genetic algorithm works more slowly than the ANFIS method.
2- If the objective function is well-behaved and relatively uniform, the ANFIS method is a better option.
3- The existence of the fitness operator in the genetic algorithm and the effect of its choice on the optimal response is another reason that enhances the use of the ANFIS method, because if the fitness operator is not selected well and strong, then the solutions obtained from the genetic algorithm cannot be considered as optimal ones.
4- Although the genetic method is a random search method and has a possibility of low-response blocking (parameter values) at the optimal localized points, it has a significant error in the estimation of the output variable data. However, this error is minimal using fuzzy if-then rules in the ANFIS method.
5- On the other hand, ANFIS is one of the fuzzy-neural hybrid models in which the neural network and the fuzzy system are combined in a coordinated structure. This combination improves network performance and enhances the learning potential of the neural network.
6- In fact, ANFIS is employed to solve nonlinear regression and estimate functions. In addition, the ANFIS method generates very low estimation error.

Although there are several mathematical models for estimating fuel cell parameters, the main objective of the present study is to evaluate the soft computing methods for tackling the performance prediction of fuel cells. ANFIS method has the ability to learn and predict. It can deal with encountered uncertainties for different systems. In the present study, the most effective parameters of a fuel cell are determined by the ANFIS method . Accordingly, this paper is outlined by giving an introduction, a methodology (modeling the PEM fuel cell and developing the ANFIS method), presenting, analyzing, and discussing the results followed by conclusion.

2. METHODOLOGY

2.1. PEM fuel cell model

In this research work, the model proposed by Priya et al. [13] is implemented. Output voltage can be obtained by adding the equilibrium potential, which is denoted by E_{Nernst}, and also drops of voltage. There are different voltage drops in cells including activating, V_{act}, Ohmic, V_{Ohmic}, cross over, and mass transport V_{con}. Hence, the output voltage can be calculated as follows: $V_{fc} = E_{Nernst} - V_{act} - V_{Ohmic} - V_{con}$.

The crossover drop is usually neglected, because their values are small. The equilibrium potential, E_{Nernst}, can be calculated as follows [13]:

$$E_{Nernst}=1.229-0.85\times10^{-3}(T-298.15)+4.3085\times10^{-5}\times T[\ln(P_{H_2})+0.5\ln(P_{O_2})] \quad (1)$$

The activation losses are shown by coefficients ε_1, ε_2, ε_3, and ε_4, which can be calculated as follows [2]:

$$V_{act}=\varepsilon_1+\varepsilon_2 T+\varepsilon_3 T\ln(C_{O_2})+\varepsilon_4 T\ln(i) \quad (2)$$

The Ohmic losses can be obtained by the following [13]:

$$V_{Ohmic}=i(R_m+R_c) \quad (3)$$

where

$$R_m=\frac{\rho_m l}{A} \quad (4)$$

$$\rho_m=\frac{181.6[1+0.03(\frac{i}{A})+0.062(\frac{T}{303})^2(\frac{i}{A})^{2.5}]}{[\lambda-0.634-3(\frac{i}{A})]\exp[4.18(\frac{T-303}{T})]} \quad (5)$$

Concentration voltage losses can be calculated as follows [13]:

$$V_{con}=-b\ln(1-\frac{I}{I_{max}}) \quad (6)$$

Therefore, the total output voltage is given by [13]:

$$\begin{aligned}V_{fc}=&N_S\times((1.229-0.850\times10^{-3}(T-298.15)+\\&4.3085\times10^{-5}\times T[\ln(P_{H_2})+0.5\ln(P_{O_2})])\\&-(\varepsilon_1+\varepsilon_2 T+\varepsilon_3 T\ln(C_{O_2})+\varepsilon_4 T\ln(i))-i(R_m+R_c)\\&+b\ln(1-\frac{I}{I_{max}})\end{aligned} \quad (7)$$

2.1.1. Problem definition

For developing an acceptable model, it is necessary for the simulated and actual characteristics to be in agreement. Priya et al. [13] used the V–I and P–I characteristics for exemplifying the problem formulation.

The DC power output can be given by [13]:

$$P=VI \quad (8)$$

Using the differential form of the above equation, the following can be written [13]:

$$\frac{dP}{dI}=V+I\frac{dV}{dI} \quad (9)$$

$$\left.\frac{dV}{dI}\right|_{mpp}+\left.\frac{V}{I}\right|_{mpp}=0 \quad (10)$$

Defining the objective function of the problem [13]:

$$\text{Minimize}(J)=\left|\frac{dV}{dI}\right|_{(V_{mpp},I_{mpp})}+\frac{V_{mpp}}{I_{mpp}} \quad (11)$$

subject to the following constraints:

$$-1.20\le\varepsilon_1\le-0.80$$
$$0.0008\le\varepsilon_2\le0.006$$
$$0.000035\le\varepsilon_3\le0.0001$$
$$-0.0003\le\varepsilon_4\le-0.00008$$
$$0.01\le b\le0.60$$
$$0.00008\le R_c\le0.00099$$
$$10\le\lambda\le24.0$$

The value of $\left|\frac{dV}{dI}\right|_{(V_{mpp},I_{mpp})}$ in Equation (11) can be determined by differentiating the basic voltage Equation (7) as follows [13]:

$$\left|\frac{dV}{dI}\right|_{(V_{mpp},I_{mpp})}=-\left[\begin{array}{l}(\varepsilon_4\frac{T}{I_{mpp}})+(\frac{b}{I_{max}-I_{mpp}})+\\(R_c+(\frac{l\times181.6}{A\exp(\frac{4.18(T-303)}{T})}))\times\Gamma\end{array}\right] \quad (12)$$

$$\Gamma=\frac{((\lambda-0.634)+J_p(0.6\lambda-0.038)+J_p^{2.5}\Delta T^2(0.217\lambda-0.1375-0.465J_p)-0.9J_p^2)}{(\lambda-0.634-3J_p)^2} \quad (13)$$

$$J_p=\frac{I_{mpp}}{A} \quad (14)$$

$$\Delta T=\frac{T}{303} \quad (15)$$

where

$$\Gamma=\frac{((\lambda-0.634)+J_p(0.6\lambda-0.038)+J_p^{2.5}\Delta T^2(0.217\lambda-0.1375-0.465J_p)-0.9J_p^2)}{(\lambda-0.634-3J_p)^2} \quad (16)$$

and

$$J_p=\frac{I_{mpp}}{A},\ \Delta T=\frac{T}{303} \quad (17)$$

Although many parameters affect fuel cells' performance, seven parameters are introduced as the inputs in this research. Table 1 illustrates seven parameters including inputs and output. The output parameter of fuel cell is determined by measurements [13].

Table 1. The inputs and output parameters.

Input/output	Parameters
Input No. 1	ε_1
Input No. 2	ε_2
Input No. 3	ε_3
Input No. 4	ε_4
Input No. 5	b
Input No. 6	R_c
Input No. 7	λ
Output	$\text{Minimize(J)}=\left\|\frac{dV}{dI}\right\|_{(V_{mpp},I_{mpp})}+\frac{V_{mpp}}{I_{mpp}}$

2.2. ANFIS method

Jang introduced the ANFIS method in 1993 for the first time by combining ANN with FIS to resolve the shortcoming of two individual methods of ANN and FIS. The rules of ANFIS can be developed during the process of training [46].

Figure 1 shows the ANFIS fuzzy structure in which five layers are used for constructing the inference system. There are several fixed and adjustable nodes that operate as membership functions (MFs) and the rules in the hidden layers. For explaining the procedures of the ANFIS model, there are two inputs of x and y and, also, one output, as illustrated in Fig. 1. Generally, in the ANFIS, the relationship between input and output is shown by "if-then" rules. Therefore, the rules for the inference system of Takagi and Sugeno [47] can be used for the following structure:

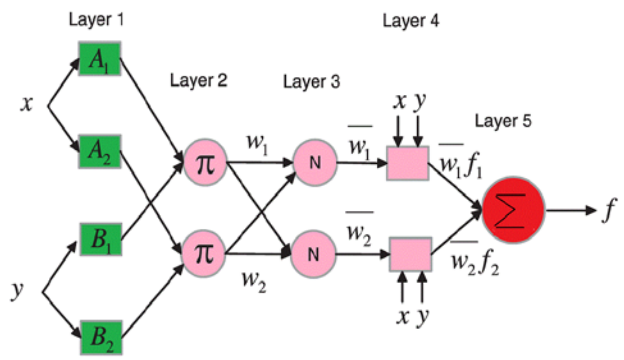

Figure 1. The structure of ANFIS [47].

The MATLAB software was used for developing and training the ANFIS model. Accordingly, the "if-then" rule proposed by the fuzzy Takagi and Sugeno inference system was used as Eq. 5 in the presence of two inputs.

$$\text{if x is A and y is C then} \\ f_1 = p_1x + q_1y + r_1 \tag{18}$$

The first layer is the fuzzification layer. This layer acts as a source of inputs required by the next layer consisting of adaptive nodes with function $O = \mu_{AB}(x)$ and $O = \mu_{CD}(x)$, where $\mu_{AB}(x)$ and $\mu_{CD}(x)$ are the membership functions. The following equation expresses the selected bell-shaped MFs with the maximum of (1.0) and minimum of (0.0) [48]:

$$\mu(x) = \text{bell}(x; a_i, b_i, c_i, d_i) = \frac{1}{1 + \left[\left(\frac{x-c_i}{a_i}\right)^2\right]^{b_i}} \tag{19}$$

where $\{a_i, b_i, c_i, d_i\}$ represents a set of functional parameters, which in this layer are selected to act as premise parameters, and x represents the inputs.

The purpose of the second layer is to determine and incorporate the weight of each membership function. This layer involves non-adaptive nodes that receive the signals sent by the previous layer and represent the membership functions of fuzzy sets related to each input. In this layer, the received signals are multiplied and, then, forwarded as follows: $w_i = \mu_{AB}(x) * \mu_{CD}(y)$. Here, the efficiency of rules is illustrated by output nodes [49].

Neurons of the third layer represent the pre-conditions corresponding to the devised fuzzy rules. This layer, which can also be called the rule layer, defines the level at which each rule starts to apply; herein, the number of the mentioned rules is equal to the number of layers. The nodes of this layer, which are non-adaptive, calculate the normalized weights. Each of these nodes is tasked with calculating the efficacy value of one rule with respect to the sum of efficacy rates of all rules using the equation $w_i^* = \frac{w_i}{w_1+w_2}$, $i = 1,2$. The outputs of this step will be the normalized efficacies [47]. In the fourth layer, which is called the defuzzification layer, the outputs of the inference of rules will be provided. This layer consists of adaptive nodes with function $O_i^4 = w_i^* xf = w_i^*(p_ix + q_iy + r_i)$, where $\{p_i, q_i, r\}$ is a variable set containing the resulting parameters [50].

In the last layer, which is called the output layer, all inputs received from the previous layer will be aggregated, and resulting fuzzy classification outputs will be transformed into a crisp binary variable. This layer consists of one non-adaptive node, which computes the final output in the form of the sum of all received signals [51],

$$O_i^5 = \sum_i w_i^* xf = \frac{\sum_i w_i f}{\sum_i w_i} \tag{20}$$

In the ANFIS architectures, variables are identified by means of a hybrid learning algorithm, which passes in the fourth layer. Then, a least squares estimation scheme is used to determine the consequent variables. The backward pass propagates the error rates backwards and uses the gradient decline order to synchronize the premise variables.

3. ANALYSIS

3.1. Evaluation of accuracy indices

The performances of ANFIS models can be evaluated by the popular statistical indicators of root-mean-squared error (RMSE) and determination coefficient (R^2). These statistical indices are as follows:

1) Root-Mean-Square error (RMSE) can be obtained by [52]:

$$RMSE=\sqrt{\frac{\sum_{i=1}^{n}(P_i-O_i)^2}{n}} \tag{21}$$

2) Coefficient of Pearson Correlation (r) is as follows [52]:

$$r=\frac{n\left(\sum_{i=1}^{n}O_i.P_i\right)-\left(\sum_{i=1}^{n}O_i\right).\left(\sum_{i=1}^{n}P_i\right)}{\sqrt{\left(n\sum_{i=1}^{n}O_i^2-(\sum_{i=1}^{n}O_i)^2\right).\left(n\sum_{i=1}^{n}P_i^2-(\sum_{i=1}^{n}P_i)^2\right)}} \tag{22}$$

3) The determination coefficient (R^2) is [52]:

$$R^2 = \frac{\left[\sum_{i=1}^{n}\left(O_i-\bar{O}_i\right).\left(P_i-\bar{P}_i\right)\right]^2}{\sum_{i=1}^{n}\left(O_i-\bar{O}_i\right).\sum_{i=1}^{n}\left(P_i-\bar{P}_i\right)} \quad (23)$$

where P_i is the experimental value and O_i is the forecasting value. Moreover, n is the total number of tested data [52].

3.2. ANFIS results

In this study, seven effective parameters are considered as input variables including four semi-empirical coefficients (ε_1, ε_2, ε_3, ε_4), a parametric coefficient (b), equivalent contact resistance (R_c), and an adjustable parameter (λ). The optimal combination set of inputs was determined by performing a global search through the given inputs. This set, shown in Table 1, is in fact a set that leaves the most significant impact on the output parameter in Equation (11). The developed ANFIS model consists of a number of functions dedicated to different combinations. The models were trained with different combinations of inputs to find the effective parameters, i.e., from one input to three inputs. The output of models was evaluated by the performance factor. Accordingly, the inputs with the highest level of impact on the prediction of the output were identified. The results of these operations are presented in Tables 2 to 4. Those input variables that had the lowest training errors exhibited the highest level of relevance to the output.

Table 2 shows that, in the case of input, the most influential parameter for the fuel cell's prediction is λ (input 7) with a test error of 1.6884.

Based on Table 3, in the case of using two inputs for predicting the output value, the format of 2, 7 (a combination of ε_2 and λ) has the highest role in predicting the output with the highest accuracy and the lowest testing error (1.7544).

Table 4 illustrates that, in the case of using three inputs, the combination of 2, 3, and 7 (ε_2, ε_3, and λ) has the best response in predicting the output value by a testing error of 1.9432.

Table 2. Input influential parameter for the prediction of the fuel cell's parameters (1 input).

ANFIS model	Train	Test	Input No.	Number of inputs
1	20.6837	19.6856	1	1
2	20.4724	19.7992	2	1
3	20.5420	19.8793	3	1
4	20.7071	19.7504	4	1
5	20.5898	20.1992	5	1
6	20.6499	19.7693	6	1
7	**1.7162**	**1.6884**	**7**	**1**

The results indicated that the larger the number of inputs, the higher the training accuracy and the lower the testing accuracy. The possibility of overfitting between training and testing errors prevents the use of more than two parameters and encourages the use of simplified models. The fuel-cell parameters that are predicted (based on inputs of Table 2 to 4) by the ANFIS scatter plots are shown in Figure 2. The results showed a very good coefficient of determination, which confirmed their validity. Moreover, they proved a very limited extent of overestimation/underestimation indicating a good level of precision, most notably for the case where there was only one input.

Table 3. Influence of input parameters on the prediction of the fuel cell's parameters (2 inputs).

ANFIS model	Train	Test	Inputs	Number of inputs
1	20.0025	19.6613	1 , 2	2
2	20.1605	20.3996	1 , 3	2
3	20.2707	19.7945	1 , 4	2
4	20.0157	21.5209	1 , 5	2
5	20.1628	20.2325	1 , 6	2
6	1.6973	1.7295	1 , 7	2
7	20.0794	20.0625	2 , 3	2
8	20.2801	20.2801	2 , 4	2
9	20.1772	20.4948	2 , 5	2
10	20.2099	19.9632	2 , 6	2
11	**1.6547**	**1.7544**	**2 , 7**	**2**
12	20.4876	20.0335	3 , 4	2
13	20.3617	20.3443	3 , 5	2
14	19.9990	20.6101	3 , 6	2
15	1.6685	1.8068	3 , 7	2
16	20.5094	20.2974	4 , 5	2
17	20.5957	19.7282	4 , 6	2
18	1.7137	1.6859	4 , 7	2
19	20.4619	20.5025	5 , 6	2
20	1.6846	1.7552	5 , 7	2
21	1.7075	1.6645	6 , 7	2

Table 4. Influence of input parameters on the prediction of the fuel cell's parameters (3 inputs).

ANFIS model	Train	Test	Inputs	Number of inputs
1	19.12	20.75	1 , 2 , 3	3
2	19.58	19.74	1 , 2 , 4	3
3	18.71	21.53	1 , 2 , 5	3
4	19.16	20.34	1 , 2 , 6	3
5	1.62	1.79	1 , 2 , 7	3
6	19.57	20.64	1 , 3 , 4	3
7	19.36	22.41	1 , 3 , 5	3
8	19.35	21.36	1 , 3 , 6	3
9	1.61	1.84	1 , 3 , 7	3
10	19.20	22.98	1 , 4 , 5	3
11	19.53	21.10	1 , 4 , 6	3
12	1.62	1.82	1 , 4 , 7	3
13	19.33	22.38	1 , 5 , 6	3
14	1.54	1.99	1 , 5 , 7	3
15	1.61	1.76	1 , 6 , 7	3
16	19.85	20.46	2 , 3 , 4	3
17	19.45	21.03	2 , 3 , 5	3
18	19.33	21.04	2 , 3 , 6	3
19	**1.54**	**1.94**	**2 , 3 , 7**	**3**
20	19.89	20.96	2 , 4 , 5	3
21	19.89	19.99	2 , 4 , 6	3
22	1.62	1.76	2 , 4 , 7	3
23	19.77	21.23	2 , 5 , 6	3
24	1.54	1.84	2 , 5 , 7	3
25	1.61	1.76	2 , 6 , 7	3

26	20.16	20.78	3 , 4 , 5	3
27	19.62	21.49	3 , 4 , 6	3
28	1.64	1.89	3 , 4 , 7	3
29	19.86	20.72	3 , 5 , 6	3
30	1.56	1.94	3 , 5 , 7	3
31	1.61	1.98	3 , 6 , 7	3
32	20.31	21.04	4 , 5 , 6	3
33	1.63	1.86	4 , 5 , 7	3
34	1.63	1.79	4 , 6 , 7	3
35	1.63	1.71	5 , 6 , 7	3
36	19.12	20.75	1 , 2 , 3	3

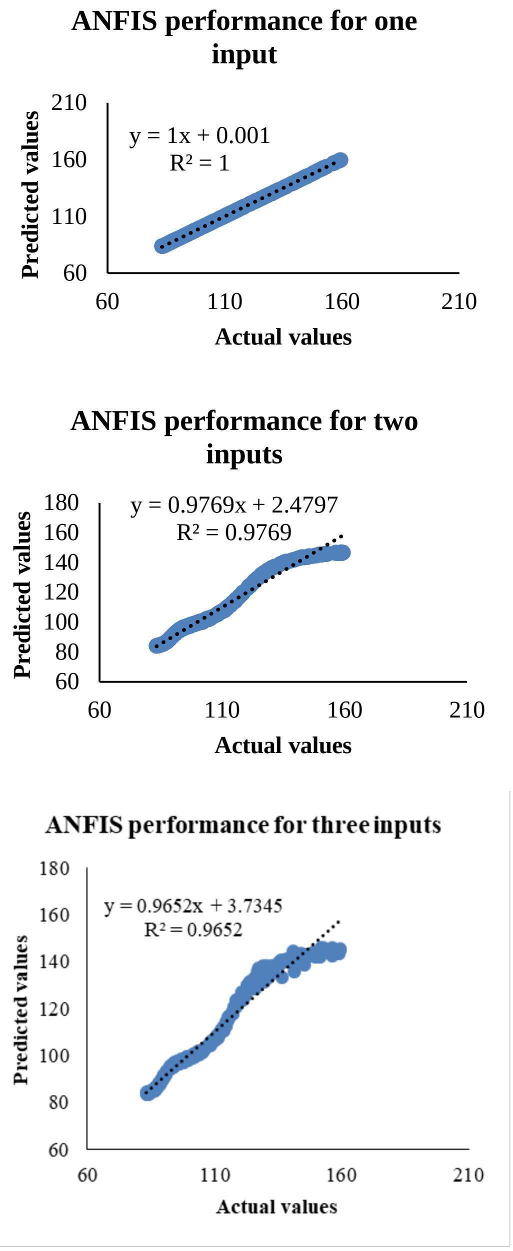

Figure 2. ANFIS scatter plots for predicting parameters of fuel cells.

As shown in Figure 1, in the case of using one input, the output of model and target value have a determination coefficient value of 1. This shows the fitting of output and target values. In the case of two and three inputs, the correlation is deviated from the linear trend. Increasing the number of inputs reduces the coefficient of determination, such that, in the case of two variables, R^2 is equal to 0.9769 and is 0.9652 in the case of three variables. Therefore, increasing the variable numbers raises the complexity of decision and evaluations.

To assess the accuracy of the predictions made by the proposed model, the error terms RMSE, r, and R^2 were calculated and compared with those of other models. A summary of the accuracy of predictions made based on the selected fuel cell parameters is presented in Table 5. As shown in Table 5, the larger the number of inputs, the more the RMSE value. The RMSE value is a factor of difference between values predicted by the model and target values [53]; therefore, it can be concluded that the larger the number of inputs, the lower the prediction accuracy.

These operations were performed to reduce the number of inputs. Reducing the number of inputs helps raise the acceleration of calculations, especially in ANFIS, because one of the important weaknesses of ANFIS is its computational time if the number of inputs is high. On the other hand, ANFIS produces more accurate outputs. In order to use the ANFIS accurately and eliminate the complexity of running the model, one of the approaches is to reduce the numbers of inputs. In the present study, the afore-mentioned method was employed to reduce the number of inputs along with keeping the model accuracy.

Table 5. Statistical results of the prediction of fuel cell's parameters for selected inputs.

One input	r	0.999995
	R^2	1
	RMSE	0.060688
Two inputs	r	0.988383
	R^2	0.9769
	RMSE	3.071737
Three inputs	r	0.982452
	R^2	0.9652
	RMSE	3.769673

4. CONCLUSIONS

The fuel cells are devices with two positive and negative electrodes called anode and cathode, which can generate electricity, from micro to mega scales, through a chemical reaction. The purpose of this study was to conduct a systematic approach of selecting the most influential parameters to anticipate parameters of fuel cells by using the ANFIS method. This method is capable of overcoming ambiguity in information and providing better conditions. Moreover, it is capable of converting the sophisticated multiple performance characteristics into a single multi index. Therefore, the method used here can enhance the multiple performances characterized for parameters of fuel cells.

The most important advantages of ANFIS are efficiency in computing, adaptation to the method optimization, and feasibility to integrate with other applications. ANFIS can be used for complex parameters, which act very fast to solve problems. For enhancing the ANFIS performance and speed, the collected database was normalized. The two main models were used as follows:

- The model that concentrates on simulation of electrochemical phenomena, heat, and mass transfer.
- The electrochemical model that is based on semi-empirical or empirical equations.

For the latest method, sets of unknown parameters (ε_1, ε_2, ε_3, ε_4, b, R_c, λ) were needed for determining accurate modeling.

For this research study, seven main parameters along with required data affecting the performance of fuel cells were identified. Then, ANFIS was performed and results were obtained in three following scenarios:

- Forecasting and selecting the most effective fuel cell parameter affecting the performance.
- Forecasting and selecting two of the most effective fuel cell parameter affecting the performance.
- Forecasting and selecting three of the most effective fuel cell parameter affecting the performance.

For demonstrating the merits of the proposed models on a more definite and tangible basis, the accuracy of prediction by different models was compared with each other. The performances of the ANFIS models for the prediction of the most influential parameters were calculated by the well-known statistical indicators of the root-mean-squared error (RMSE) and coefficient of determination (R^2). Conventional error statistical indicators, RMSE, r, and R^2 were calculated. R^2 for three different scenarios gained values of 1.000, 0.9769, and 0.9652, respectively. The R^2 values showed that ANFIS could be properly used for yielding prediction in this study.

5. FUTURE STUDY

Since there are several influential factors affecting the performance of PEMFC such as air temperature, air pressure, input relative humidity of the anode and cathode, and membrane thickness, it is suggested that researchers working in this field consider these criteria and conduct further studies to ascertain their impact on the performance of PEMFC.

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NOMENCLATURE

A	Cell active area (cm^2)
ANFIS	Adaptive neuro-fuzzy inference system
ANN	Artificial neural network
b	Parametric coefficient (V)
C_{O_2}	Oxygen concentration in catalytic interface
E_{nernst}	Thermodynamic potential of cell
GA	Genetic algorithm
I	Actual current density of the cell (A/cm^2)
I_{max}	Maximum value for I
I_{mpp}	Current at maximum power point
i_{cell}	Cell current
J	Minimization function involving the parameters
L	Thickness of PEM (cm)
N_s	Number of cells
P_{H_2}	Partial pressure for hydrogen (atm)
P_{O_2}	Partial pressure for oxygen (atm)
PEM	Proton exchange membrane
PEMFC	Proton exchange membrane fuel cell
P_{max}	Maximum value of power
R^2	coefficient of determination
R_c	Equivalent contact resistance
R_m	Equivalent membrane resistance
RMSE	Root-mean-squared error
SSO	Salp swarm optimizer
T	Cell absolute temperature (K)
V	Cell voltage (V)
V_{act}	Drop of voltage due to activation of anode and cathode
V_{con}	Diffusion potential
V_{fc}	Output voltage of fuel cell
V_{mpp}	Voltage at maximum power point
V_{Ohmic}	Ohmic voltage drop
$\varepsilon_1.\varepsilon_2.\varepsilon_3.\varepsilon_4$	Semi-empirical coefficients
Γ	Basic voltage
λ	Adjustable parameter
ρ_m	Membrane specific resistivity

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