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# Maximizing performance of fuel cell using artificial neural network approach for smart grid applications

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ABSTRACT

This paper presents an artificial neural network (ANN) approach of a smart grid integrated proton exchange membrane (PEM) fuel cell and proposes a neural network model of a 6 kW PEM fuel cell. The data required to train the neural network model are generated by a model of 6 kW PEM fuel cell. After the model is trained and validated, it is used to analyze the dynamic behavior of the PEM fuel cell. The study results demonstrate that the model based on neural network approach is appropriate for predicting the outlet parameters. Various types of training methods, sample numbers and sample distribution methods are utilized to compare the results. The fuel cell stack efficiency considerably varies between 20% and 60%, according to input variables and models. The rapid changes in the input variables can be recovered within a short time period, such as 10 s. The obtained response graphs point out the load tracking features of ANN model and the projected changes in the input variables are controlled quickly in the study.



## 1. Introduction

The fuel cell is considered an electrochemical device that generates electricity via the reaction of hydrogen and oxygen with the existence of an electrolyte. It has various advantages, such as high efficiency, fast response to load, modularity and flexibility of fuel. Some other advantages of fuel cells are reuse of the heat obtained from exhaust gases, on-site installation and fuel flexibility. The use of electrolysis to produce hydrogen from water appears to be a very efficient method for small and large scale applications [1].

Two kinds of fuel cells are expected to be used as large capacity power plants specifically solid-oxide fuel cells (SOFCs) and molten carbonate fuel cells (MCFCs) while PEM fuel cells are adequate for distributed power generation [2]. SOFC systems are mainly studied for large scale applications whereas one of the major disadvantage is to required moderate temperature values [3]. However, PEM fuel cells are mostly suggested for vehicular and household applications [4]. Achenbach [5] developed a mathematical model of a planar SOFC, which focuses on the effects of temperature changes on output voltage response. The temperature dynamics was modeled in a three-dimensional (3-D) vector space. The transient behavior of a molten carbonate fuel cell caused by impedance load change was also investigated [6]. Integration of fuel cells into smart grids is a promising opportunity for distributed power generation. Hence, there is an emerging opportunity for fuel cell systems in smart grids [7]. An efficient utilization of electricity can be achieved by using the smart grids which are designed to access energy from the most effective source at the specific time. Considering the environment, the grid needs to be accessible to all power sources, prioritizing renewable sources and local generation. From an economic standpoint, the supply is favored to be secure, reliable and cost effective [8]. Energy storage also plays a key role in the successful implementation of smart grids, because it ensures stability and reliability to the grid enabling the storage of energy when demand is low. The release of energy during peak demand periods represents an improvement step in the system's flexibility [9]. If the distributed power plants are more responsive, the smart grids can reduce the need for the base load power. This is where fuel cells can provide an extensive advantage. This helps to reduce losses from transmission distance. Integrated into a smart grid, this technology can make use of its responsiveness, while taking advantage of the higher prices during peak demand to cover the added costs [10].

Levelized cost of energy (LCE) for PEM fuel cells are very close to conventional and mature technologies such as nuclear and coal.

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Among alternative energy sources, it has second lowest LCE after wind energy [11]. In LCE calculations, the comparative cost of energy on a $USD/MWh basis is considered which accounts for the installed system price and related costs such as funding, land, insurance, transmission, operation and maintenance, and devaluation [11]. Fuel cells can offer many advantages in smart grids such as reliability which enables clean, quiet power and near 100% availability with modular installation. They are also secure for local generation applications because of being controlled locally, having shorter connection and transmission lines. Fuel cells are also flexible by which they can be grid connected, parallel, off-grid, remote or local smart controls in addition to their environmentally friendly structure [12]. Fuel cells can be used as prime power as they operate all day supplying some or all the demanded load. They can also serve as a combined heat and power unit. The fundamental idea of the smart grid is to rise the flexibility and responsiveness of the electrical grid by refining the information accessible to utility corporations. Ultimately, smart grid technology is designed to reduce inefficiencies in electricity production by better matching supply to demand. Artificial neural networks are one of the alternative methodologies to implement smart grid applications. The computational units of ANNs are named neurones and are ordered in different layers, such as the input layer, one or more hidden layers, and the output layer. Every neurone has connections, which are named weights, with every neurone in both the previous and the following layer. Furthermore, each one contents a bias that makes it work or not work based on the level of the input signal. The $i^{th}$ neurone's input is made by the mathematical combination of the weight, the bias, and the signals from the preceding neurones. After that, the input is handled by the transfer function that gives the neurone output. A feedforward neural network with biases, a Sigmoid transfer function in the hidden layer, and a linear output can estimate any actual continuous function to any accuracy on a dense set of data. Iterative calculations bring to the definition of the weights and biases. Iteration by iteration the weights and the biases are revised proportionally to the mean squared error between the calculated output and the desired targets [13].

ANN models have been utilized by many researchers in the literature. Sanchez et al. [14] proposed an adaptive B-spline neuro controller for the optimal air supply into a PEM fuel cell. Real time results of the PEM fuel cell system emulator and the neuro controller obtained by the hardware in the loop strategy were exhibited. The experimental results validate that the proposed fuel cell emulator replicates in great measure the dynamic performance of the PEMFC. El-Sharkh et al. [15] presented a neural network (NN) based active and reactive power controlling unit of a stand-alone PEM fuel cell power plant. The control activities are based on feedback signals from the terminal load, output voltage and hydrogen input. The results showed fast response of the controller to load variations, and the effectiveness of the recommended controller for controlling the active and reactive power output. Mammar and Chaker [16] indicated that back-propagation feedforward networks demonstrate acceptable performance for the prediction of cell voltage. Neural network and fuzzy logic controllers are used to control the active power of the PEM fuel cell system. They showed that neural network controller and fuzzy logic controller are very operative to control hydrogen flow for active power load variation. Bhagavatula et al. [17] used ANN approach for predicting the voltage-current characteristics of a PEM fuel cell. They utilized experimental data to train the model and compared the accuracy of the results. Rezazadeh et al. [18] considered averaged cell voltage as the output, the current density and the cell temperature as the inputs of neural networks in their study. They utilized experimental data for training and testing the networks. The attained results showed that enhanced neural network models may effectively estimate the averaged cell voltage and they yield higher accuracy than other modelling options particularly in the low current section of fuel cell operation. Hatti and Tioursi [19] studied the artificial intelligence methods to control a PEM fuel cell structure, principally using a practise of dynamic neural network. The simulation results demonstrated that the model-based dynamic neural network control system is suitable for controlling. Ahmed and Ullah [20] studied dynamic model of SOFC system. They compared the model with PI controllers and analyzed the noise impacts together with robustness. Midilli and Dincer [21] studied exergy based parameters for PEM fuel cells to investigate the effect of operating aspects and system characteristics on the environment and sustainability. It was suggested that, in order to predict the micro-level influence of a PEM fuel cell on the environment and macro level sustainability, the proposed exergy based parameters need to be employed for practical systems. Ozbilen et al. [22] applied an ANN method to a nuclear-based hydrogen production system and presented that the ANN model can straightforwardly be used to calculate environmental impacts for nuclear-based thermochemical hydrogen production and the efficiency of the plant. ANN models are extensively utilized in many areas, ranging from material processing to batteries. Benyounis and Olabi [23] made a review study to indicate the application of ANN into the welding process. Their study revealed the high level of interest in the adaptation of RSM and ANNs to predict response and optimize the welding process. The application of ANN into the optimization of CO2 laser welding was also studied by Olabi et al. [13]. They implied that in case of lack of experimental data, ANN can help to investigate the models.

PEM fuel cell model simulations can support in examining the chemical reactions within the fuel cell and in understanding, prediction, control and optimization of the transport effects, liquid formation and electrochemical actions in PEM fuel cells [24]. Carton and Olabi [24,25] developed a 3-D model of PEM fuel cell by using non-conventional flow plate material. They obtained IV-curves from the developed model and experimental setup to compare the results. The developed model was validated by comparing simulated IV-curve results against experimental results where the polarization curves have a good match with experimental results.

Recently, the distributed generation systems, which can be efficiently combined into micro-grids, emerge as new research area. The control logic in determining the micro-grid performances and consistency is significant and can be enhanced by applying advanced control methods such as model predictive control. Bruni et al. [26,27] implemented a control logic for a house, including a fuel cell. They applied deterministic and stochastic model predictive control to the system and compared the results with model predictive control to a standard rule based control logic. They resulted that deterministic model predictive control algorithm can realize good performance for thermal control denoting a fairly small total error caused by weather forecast inaccuracies.

In this study, an artificial neural network (ANN) model of a smart grid integrated 6 kW PEM fuel cell is studied. ANN considers fuel inlet flow rate, air inlet flow rate and stack temperature as inputs and fuel cell voltage, current and efficiency as outputs. The data required to train the neural network model are generated by a built-in model of 6 kW PEM fuel cell in MATLAB/Simulink software. Each data set consists of different number of data samples for each input variable. Different types of training methods namely Levenberg–Marquardt and Bayesian regulation, sample numbers and sample distribution methods are utilized to compare the results under different design conditions.

## 2. System description

The system consists of a PEM fuel cell, power control unit (PCU) which includes filter and DC/DC converter as shown in Fig. 1. In MATLAB software, a PEM fuel cell model with multiple power outputs is available. This built-in fuel cell model has been used in many studies in the literature and validated by different approaches [28–30].

The simplified model of fuel cell in MATLAB represents a particular fuel cell stack operating at nominal conditions of temperature and pressure. The parameters of the equivalent circuit were modified based on the polarization curve obtained from the manufacturer datasheet which is NetStack PS6 data sheet [31,32]. Using the parameters from the datasheet, the polarization curve of the stack operating at fixed nominal rate of conversion of gases is closed to the datasheet curves as shown in Fig. 2. The dotted lines show the simulated stack voltage and the simulated stack power whereas straight lines show the actual stack voltage and power. Above the maximum current, the flow rate of gases entering the stack is maximum and the stack voltage decreases sharply as more current is drawn.

The following assumptions are made for the embedded PEM fuel cell model in MATLAB:

- The gases are ideal.
- The stack is fed with hydrogen and air.
- The stack is equipped with a cooling system which maintains the temperature at the cathode and anode exits stable and equal to the stack temperature.
- The stack is equipped with a water management system to maintain the humidity inside the cell at appropriate level at any load.
- The cell voltage drops are due to reaction kinetics and charge transport as most fuel cells do not operate in the mass transport region.
- Pressure drops across flow channels are negligible.
- The cell resistance is constant at any condition of operation.

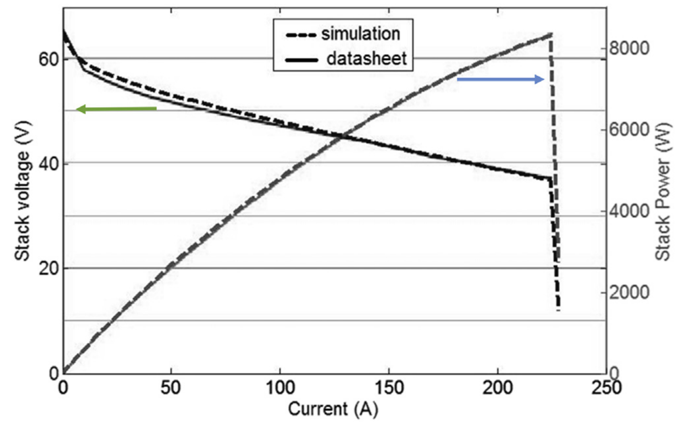


**Fig. 2.** Comparison of polarization curves of MATLAB PEM fuel cell model and NetStack PS6 PEM fuel cell (data from Ref. [29]).

This model is adapted by adding inputs, outputs and scope screens. The fuel cell is controlled to produce maximum power by the neural network model to meet the system's required power demand. The neural network model for fuel cell receives the fuel flow rate, air flow rate and cell temperature as inputs. After ANN is trained and the MATLAB/Simulink model is generated, it is connected to the inputs of fuel cell model and scope screens.

In order to train the neural network, random inputs are supplied to PEM fuel cell model by using random number generation within the range of commercial fuel cell parameters. The random number block generates normally distributed random numbers using 'randn' function in MATLAB. The random number block outputs a real signal of type double. The output is repeatable for a given seed. The saturation filters are also utilized to limit lower and upper input values. In the simulation process of some cases, rump functions having constant slopes and initial values are applied as inputs to understand and compare the obtained results with the existing model outputs and generated ANN outputs in the software. The rump function scans the full range of the input parameters. There is

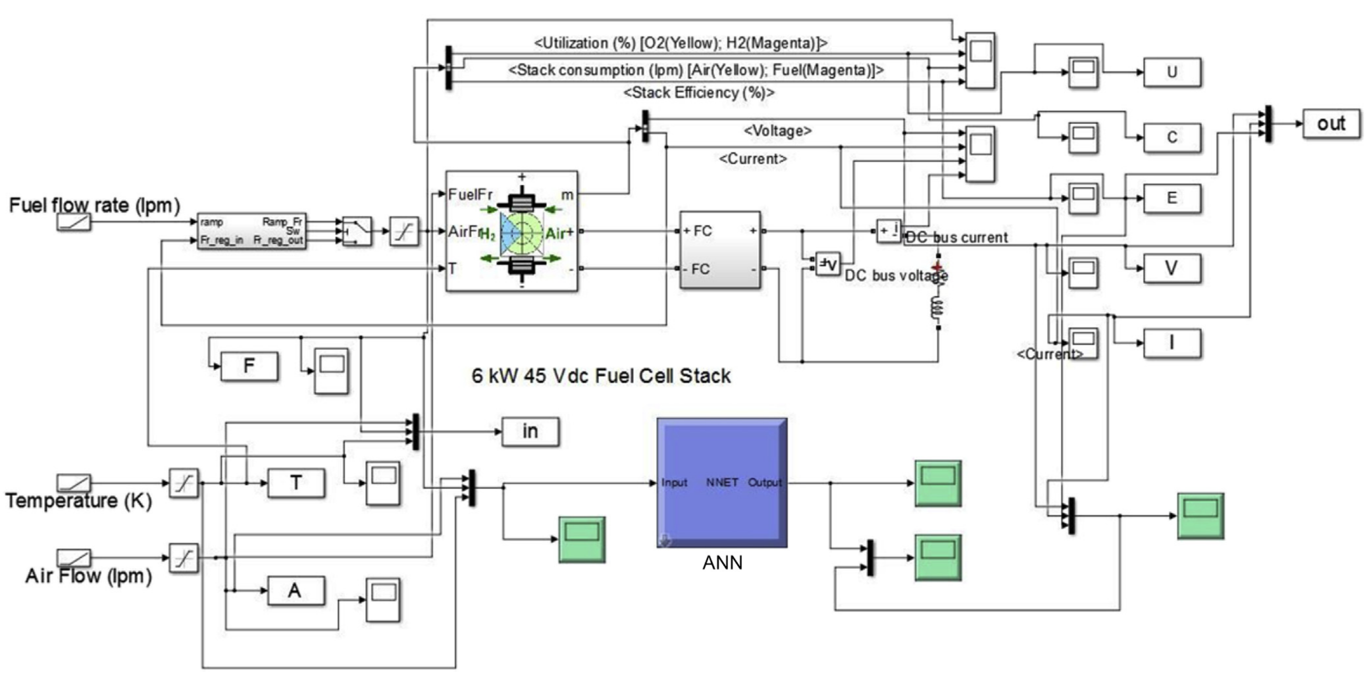


**Fig. 1.** PEM fuel cell model in MATLAB/Simulink and artificial neural network model.

100 V DC/DC converter in the system. All output variables such as fuel utilization factor, fuel consumption, efficiency, voltage and current are scoped and data are transferred to the MATLAB workspace.

## 3. Analysis

The performance of fuel cells is affected by operating conditions and state properties. Reducing the current density rises the cell voltage and resulting in an increase in the efficiency of a fuel cell. One of the significant operational variables is the reactant use, $U_f$, denoting to the fraction of the total fuel (or oxidant) introduced into a fuel cell that reacts electrochemically as follows [33];

$$U_f = \frac{q_{H2}^{in} - q_{H2}^{out}}{q_{H2}^{in}} \tag{1}$$

where $q_{H2}$ is the hydrogen molar flow.

Higher utilization factors are expected since they lessen the essential fuel and oxidant flow, for a minimum fuel cost and compressor load and size. Nevertheless, if utilization factors are too much higher, noteworthy voltage drops are observed. The Nernst's equation and Ohm's law govern the mean voltage of the fuel cell stack.

Applying Nernst's equation and Ohm's law by accounting for ohmic, concentration and activation losses, the stack output voltage is represented as follows [33]:

$$V_{dc} = V_o - I_r - V_{act} - V_{con} \tag{2}$$

and

$$V_o = N_o\left(E^o + \frac{RT^o}{2F}\frac{\ln x_{H2} x_{O2}^{\frac{1}{2}}}{\ln x_{H2O}}\right) \tag{3}$$

Here, $V_o$ is the open circuit voltage [33]. As the reactant is used up at the electrode by electrochemical reaction, there is a potential loss aspect because of the incapability of the adjacent material to preserve the original concentration of the bulk fluid defined as concentration losses. The activation polarization is existing when the ratio of an electrochemical reaction at an electrode surface is controlled by sluggish electrode kinetics. The ohmic losses happen due to resistance to the flow of ions in the electrolyte and resistance to flow of electrons through the electrode materials.

### 3.1. Artificial neural network (ANN) model

An artificial neural network is a type of artificial intelligence method that imitates the behavior of the human brain. The approximation of any linear or nonlinear function is quite effective. Neurons used in networks are computational features which are nonlinear and typically analog. Among numerous neural network models, multi-layer perceptron models are well known potential models, which are easy to realize with hardware or software, and have powerful computational capability and extensive uses. Feed Forward Backpropagation (FFBP) for a multilayer perceptron network is the most common algorithm in the literature used for predictions with high accuracy [34]. ANN includes three main parts; inputs, hidden layer and outputs. Based on the given input and target data sets, the outputs are generated with the respect of many mathematical equations used in each hidden layer as transfer functions.

In a previous study by Taheri and Mohebbi [35], in order to find the input and output values of neural network, experimental fuel cell performance data is extracted from the open literature. They varied the temperature from 313.15 to 353.15 K. The other data set contained cell performance data for a hydrogen-feed PEM fuel cell operated at five temperature levels (from 313 to 353 K) and five pressure levels (from 0.54 to 2.5 atm). Besides, it was previously explained that the pressure does not have a main role in the results of the fuel cell [25]. Carton and Olabi [25] showed that the key issue influencing the voltage was higher oxygen flow rates and the key aspect in fuel efficiency is the hydrogen flow rate. Generally, ANN performs well in interpolation rather than extrapolation, hence, the recall data are better to be in the range of training data in order to achieve a better prediction.

In the current study, a MATLAB/Simulink model of PEM fuel cell is used to obtain required data sets. As seen in aforementioned fuel cell equations, most critical input parameters of a fuel cell are fuel flow rate, air flow rate and cell temperature. Therefore in this study, these selected parameters are varied in the range of current industrial PEM fuel cells. Operating temperature for a PEM fuel cell changes between 273 K and 353 K. Therefore, a temperature range of 283 K–350 K is taken as temperature input. Fuel flow rate changes between 0 and 150 L $m^{-1}$. The air flow rate range is taken to be between 200 L $m^{-1}$ and 400 L $m^{-1}$. The utilized ranges of the input variables are shown in Table 1. The critical outputs of a fuel cell are voltage, current and efficiency values which define the power output from a fuel cell. Therefore, these three parameters are taken as outputs of the fuel cell model. PEM Fuel Cell model in MATLAB is shown in Fig. 1 and the properties of PEM fuel cell are given in Table 2. As shown in Table 2, the PEM fuel cell nominal power is 6 kW with 65 cells, open circuit voltage is 1.12 V, fuel supply pressure is 1.5 bar and air supply pressure is 1 bar. The dynamic behavior of the PEM fuel cell depends on changes in the output current of the fuel cell. Hence, the output current is fed back to the model. PEM fuel cell stack model is connected to 100 $V_{dc}$ DC/DC converter. The converter is loaded by an RL (Resistance-Inductance) element of 6 kW with a time constant of 1 s.

### 3.2. Training of the neural network model

The data used for training the neural network model is obtained from the model of the PEM fuel cell in the MATLAB/Simulink software. Three input-output data sets with different values are used as the training data sets. Each data set consists of different number of data samples for each input variable. The Levenberg–Marquardt backpropagation algorithm and Bayesian regulation are used for training, which is performed using the neural network toolbox of MATLAB/Simulink. ANN is proposed as 2 hidden layers, 3 inputs and 3 outputs as shown in Fig. 3. The number of hidden neurons in the hidden layer may vary and affects the quality of the ANN. Therefore, an optimal number of hidden neurons needs to be determined for each neural network to achieve the best performance using by a trial and error method. During training, the error function is reduced as the number of training epoch increases. Testing data set is carried out to define when to end training process by checking the error of the test data. The error from the test data is usually less than that from the training data. After the ANN is trained, the model is complete to provide forecasts

**Table 1**
Range of input variables used for training the ANN model in the study.

| Input variable | Minimum | Maximum |
|---|---|---|
| Fuel flow rate (L $m^{-1}$) | 0 | 150 |
| Air flow rate (L $m^{-1}$) | 200 | 400 |
| Temperature (K) | 283 | 350 |

**Table 2**
Nominal parameters and specifications of PEM fuel cell model.

| | | |
|---|---|---|
| Stack Power | Nominal (W) | 5998.5 |
| | Maximal (W) | 8325 |
| Fuel cell resistance (Ω) | | 0.0783 |
| Nernst voltage of one cell (V) | | 1.1288 |
| Nominal Utilization | Hydrogen (%) | 99.56 |
| | Oxygen (%) | 59.3 |
| Nominal Consumption | Fuel (L $m^{-1}$) | 60.38 |
| | Air/(L $m^{-1}$) | 143.7 |
| Exchange current density (A) | | 0.2919 |
| Exchange coefficient | | 0.6064 |

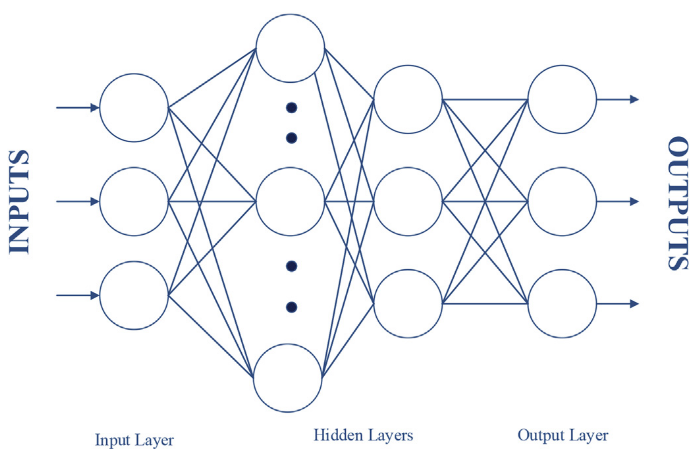


**Fig. 3.** Proposed artificial neural network system with three inputs - three outputs.

of output variables are then compared to the experimental ones in the validated data set to assess the performance of the ANN model. In ANN, the validation data are not used in training process however testing data is also included in the training. Hence, the model is trained appropriately and tested sufficiently with intermediate data to confirm the correct training and lastly validated with remaining percentage (15% for the case studies) of the input data.

## 4. Results and discussion

In MATLAB/Simulink neural network toolbox, mean squared error is the average squared difference between outputs and targets, lower values are preferred for high performance network training. In the designed ANN, it is aimed to reach the minimum mean squared error by varying the parameters. Regression (R) values measure the correlation between outputs and targets. R value of 1 means a close relationship, R value of 0 means a random relationship. In order to find best training method, best training data distribution and the best number of samples, a comparative study, including the cases shown in Fig. 4, is undertaken. The selected parameters directly affect the performance of the training and accuracy of the model.

### *4.1. Results of training neural network for different number of hidden layers*

The results for different number of hidden layers with three inputs and three outputs are shown in Table 3. The training method is Levenberg-Marquardt and 151 data samples are used. 70% of samples is used for training, 15% is used for testing, and 15% is used for validation. As seen in Table 3, minimum accumulated error is observed in 20 hidden layers. A network with a different number of hidden neurons in the input layer is tried, and finally the number of

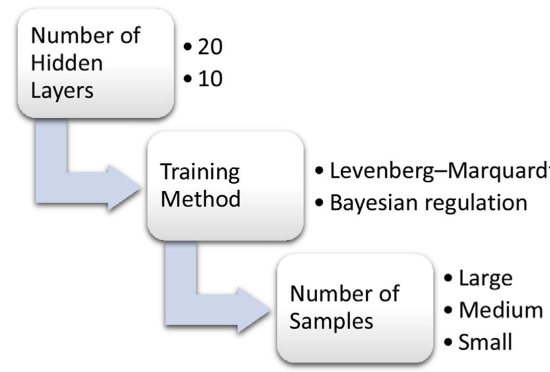


**Fig. 4.** Selected variations for training the ANN model.

hidden neurons selected in the first layer is set to 20.

### *4.2. Effect of training method on training performance*

In order to see the effect of two different types of training methods, a number of trainings were realized. In this case, 70% of 151 samples is used for training, 10% is used for testing, and 20% is used for validation. The number of hidden layers are fixed in 20. The results are shown in Table 4. In comparison with Levenberg-Marquardt (LM) training method, Bayesian Regularization (BR) showed better regression and validation performance by having less error.

### *4.3. Comparison of neural network results with fuel cell model simulation results*

After trials related to different training methods, number of hidden layers and data distribution, parameters indicated in Table 5 are applied. The summary of the obtained results is given in Table 6. The figures indicate the inputs to the neural network and outputs from neural network and from the MATLAB/Simulink model. In all cases, 70% of data samples is used for training, 15% is used for testing, and 15% is used for validation.

The input parameters to ANN are chosen as fuel flow rate, air flow rate and stack temperature. In the proposed cases, these variables are adjusted in the range of commercial PEM fuel cell applications. In Case 1, in order to observe the effect of changing fuel flow rate, fuel flow is linearly increased to 85 L $m^{-1}$. Temperate is increased from 290 K to 350 K and air flow rate is adjusted between 150 L $m^{-1}$ and 400 L $m^{-1}$ as shown in Fig. 5. The simulation results and ANN outputs are illustrated in Fig. 6. The current increases up to 138 A. The stack efficiency does not change sharply within 10 s. The voltage remains nearly constant at 43 V till 10 s. After the fuel flow rate is increased from 50 L $m^{-1}$ to 80 L $m^{-1}$ within less than 5 s, although voltage increases to approximately 60 V, current decreases to 102 A. Hence stack efficiency decreases to 38% from 60% peak cell efficiency. In order to see the effect of changing parameters to trained ANN, different inputs as shown in Fig. 7 are fed to ANN model and fuel cell model. In this case, ANN outputs are very close to simulation outputs and after 10 s, they fully match as seen in Fig. 8.

In Case 2, the simulation time is increased to 50 s. In Fig. 9, air flow rate rises from 200 L $m^{-1}$ to 400 L $m^{-1}$ within 50 s. The temperature ranges between 290 K and 350 K. The fuel flow rate is increased to 150 L $m^{-1}$ within 33 s. As shown in Fig. 10, Case 2 can follow the simulation results very well. The increase in voltage and decrease in current values are more linear. The outputs of ANN model are equal to simulation outputs. However in this case, stack

**Table 3**
Training results for different number of hidden layers.

| Number of hidden layers | Error (Accumulated around) | Best validation performance MSE | Number of epochs | Regression (Training, validation, test) |
|---|---|---|---|---|
| 10 | −0.00233 | 1.2721 | 165 | 0.99989 |
| 15 | 1.276 | 51.7057 | 15 | 0.99651 |
| 20 | −0.00022 | 2.2278 | 10 | 0.99759 |

**Table 4**
Training results for different training methods.

| Training method | Error (Accumulated) | Best validation performance MSE | Number of epochs | Regression (Training, validation, test) |
|---|---|---|---|---|
| Levenberg-Marquardt | 0.09894 | 0.019619 | 191 | 0.99999 |
| Bayesian Regularization | 0.002268 | 8.98e-05 | 1000 | 1 |

**Table 5**
Selected cases for the training of the ANN model.

| Case/Model number | Number of hidden layers | Training method | Number of samples |
|---|---|---|---|
| 1 | 20 | Levenberg–Marquardt | 25,314 |
| 2 | 20 | Levenberg–Marquardt | 524 |
| 3 | 20 | Bayesian regulation | 524 |
| 4 | 20 | Bayesian regulation | 50,273 |
| 5 | 20 | Bayesian regulation | 50,273 |
| 6 | 10 | Bayesian regulation | 50,273 |

**Table 6**
Parameters and results of different trainings and number of hidden layers.

| Model case Nr. | Nr. of hidden layers | Training method | Nr. of samples | Error | Best validation Perf. MSE | Nr. of epoch | Regression (Training, validation, test) |
|---|---|---|---|---|---|---|---|
| 1 | 20 | LM | 25,314 | 0.6944 | 4.80E-01 | 1000 | 0.99984 |
| 2 | 20 | LM | 524 | −0.03243 | 1.07E-02 | 35 | 0.99996 |
| 3 | 20 | BR | 524 | −0.00274 | 2.08E-05 | 1000 | 1 |
| 4 | 20 | BR | 50,273 | −0.00703 | 2.31E-04 | 1000 | 1 |
| 5 | 20 | BR | 50,273 | 0.5256 | 2.62E-02 | 1000 | 0.99999 |
| 6 | 10 | BR | 50,273 | 0.2768 | 2.29E-02 | 1000 | 0.99999 |

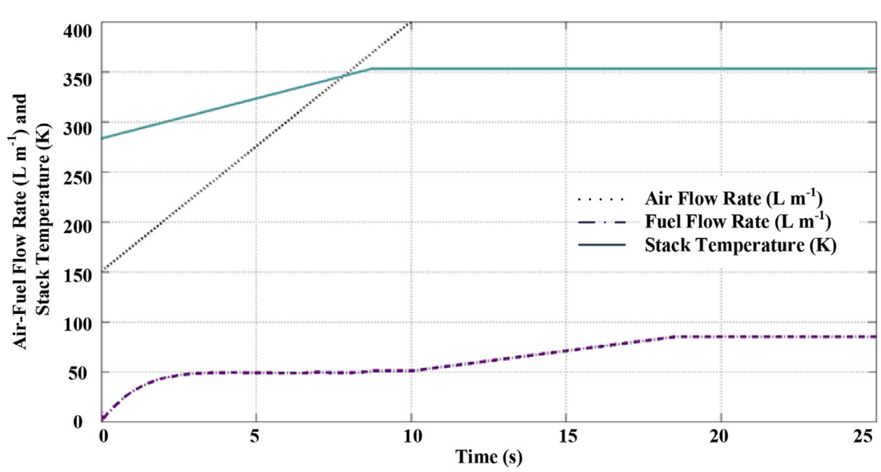


**Fig. 5.** Air flow rate, fuel flow rate and stack temperature inputs for Model 1.

efficiency decreases down to 20%. When different inputs are fed to Case 2 as seen in Fig. 11 where fuel flow rate changes at 15 s and temperature increase rate is higher, the fluctuations occur. Fig. 12 shows the outputs for the inputs given in Fig. 11. However, at 15 s, ANN model's ability to follow simulation results decrease although both simulation and ANN model results overlap after 40 s. The input shown in Fig. 11 is used for Case 3 and a better harmony between ANN model and simulation results are obtained as shown in Fig. 13. The only one difference between Case 2 and Case 3 is the method of training. The number of samples and hidden layers remain constant. Therefore, it is concluded that when ANN is trained by Bayesian Regularization method, it has higher accuracy than ANN model trained by Levenberg-Marquardt method for this specific model.

Case 4 uses Bayesian Regularization training method for the inputs given in Fig. 11 however, there are more number of samples

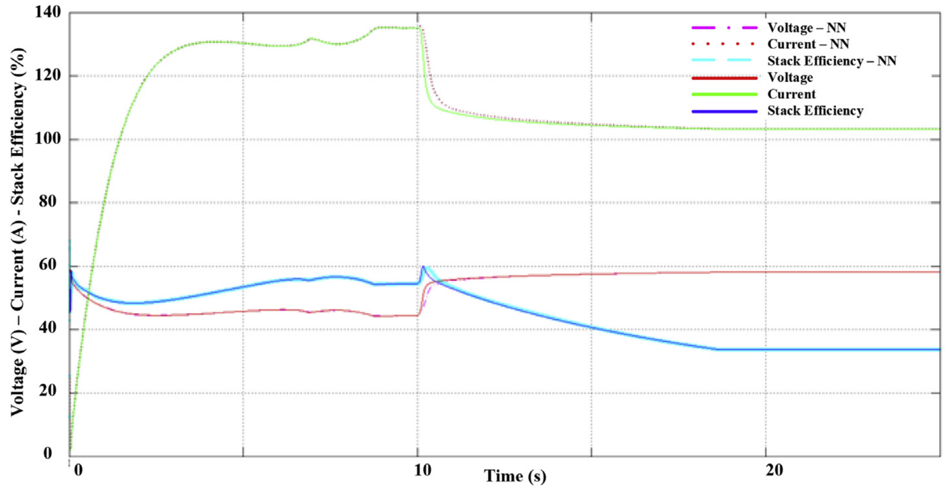


**Fig. 6.** Voltage, current and stack efficiency outputs of Model 1.

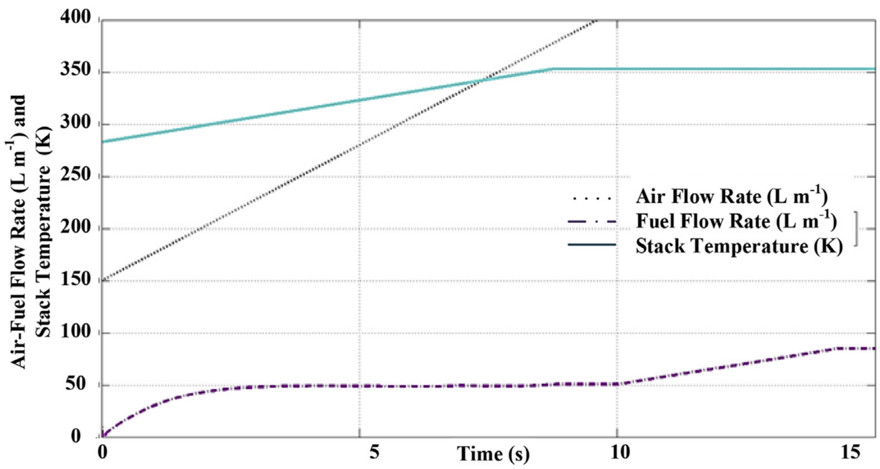


**Fig. 7.** Varied air flow rate, fuel flow rate and stack temperature inputs for Model 1.

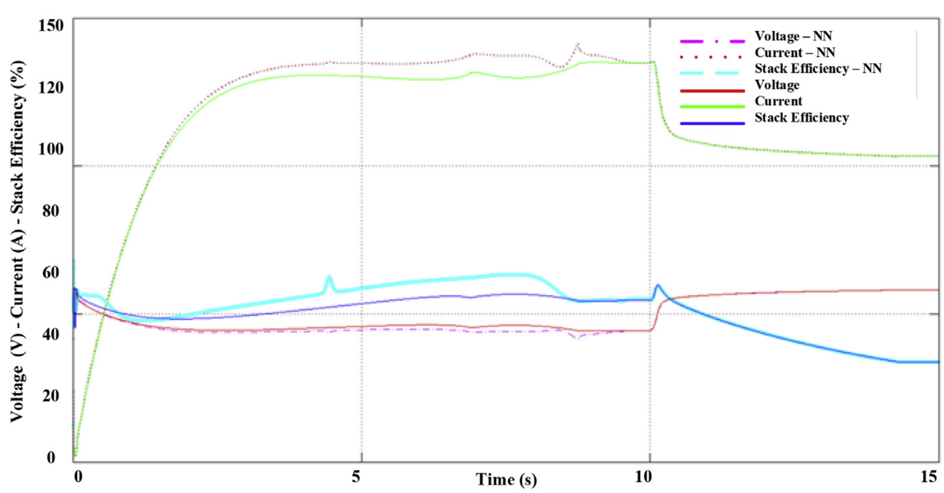


**Fig. 8.** Voltage, current and stack efficiency outputs of Model 1 for the varied inputs.

compared to Case 3. The number of samples is increased to 50,273 in order to see the effect of different sample numbers. Case 4 has similar results in terms of tracking capability with the Case 3. Although ANN model's current output is higher in Case 4, it is lower in Case 3 as shown in Fig. 14. Case 4 is trained again by Bayesian Regularization method and Case 5 is obtained. In this model, rate of change for the input variables are higher. The fuel flow rate increases to 100 L $m^{-1}$ within 7 s, temperature reaches to 350 K

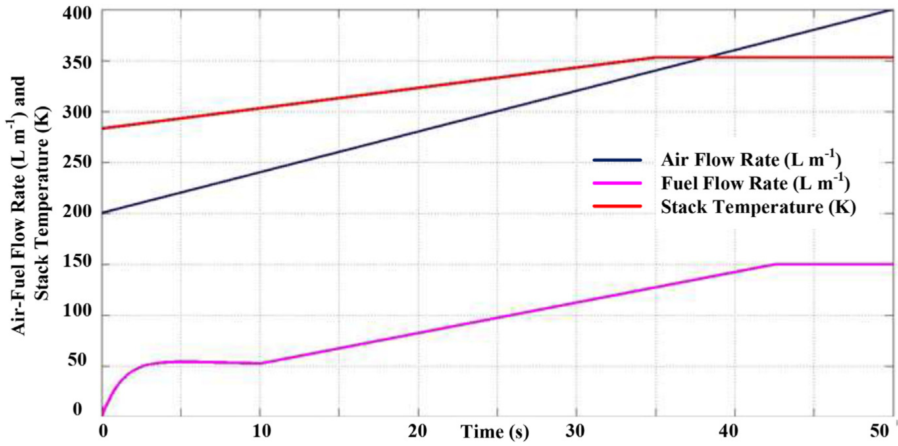


**Fig. 9.** Air flow rate, fuel flow rate and stack temperature inputs for Model 2.

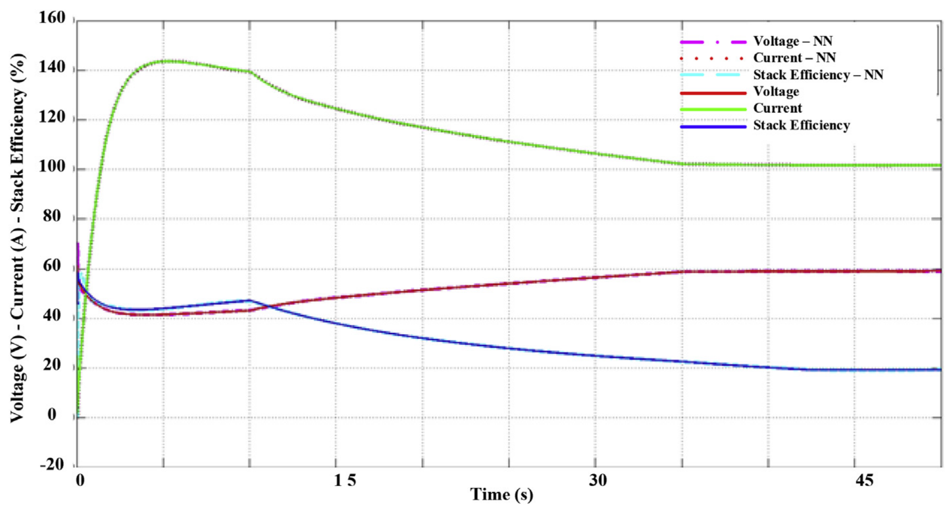


**Fig. 10.** Voltage, current and stack efficiency outputs of Model 2.

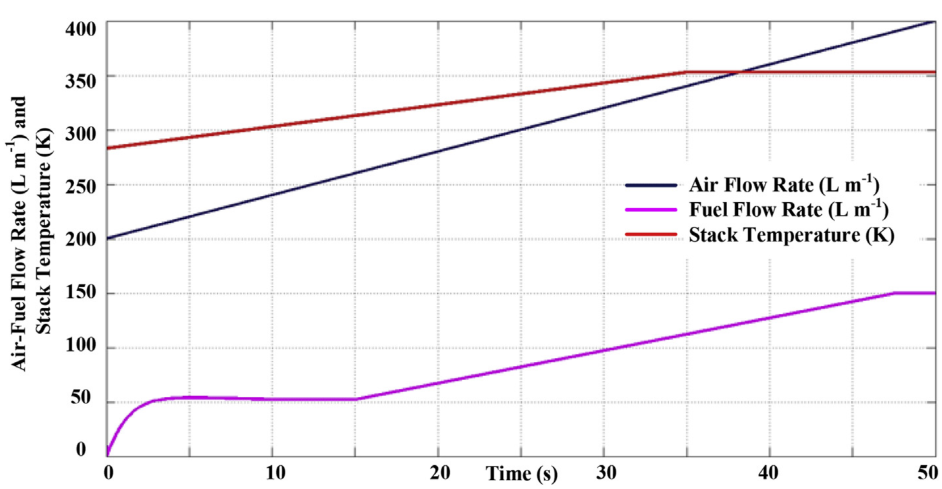


**Fig. 11.** Varied air flow rate, fuel flow rate and stack temperature inputs for Model 2.

within 7 s and air flow rate stabilizes at 33 s as shown in Fig. 15. Although sharper inputs are fed to Case 5, it has a higher accuracy compared to Case 4 as illustrated in Fig. 16. To observe the effect of changing inputs on the ANN model accuracy, inputs shown in Fig. 17 are used. As shown in Fig. 18, the ANN model can track the simulation results precisely with nearly zero error after 35 s.

Since Bayesian Regularization method yields better results, fixing training method and the number of samples, the effect of

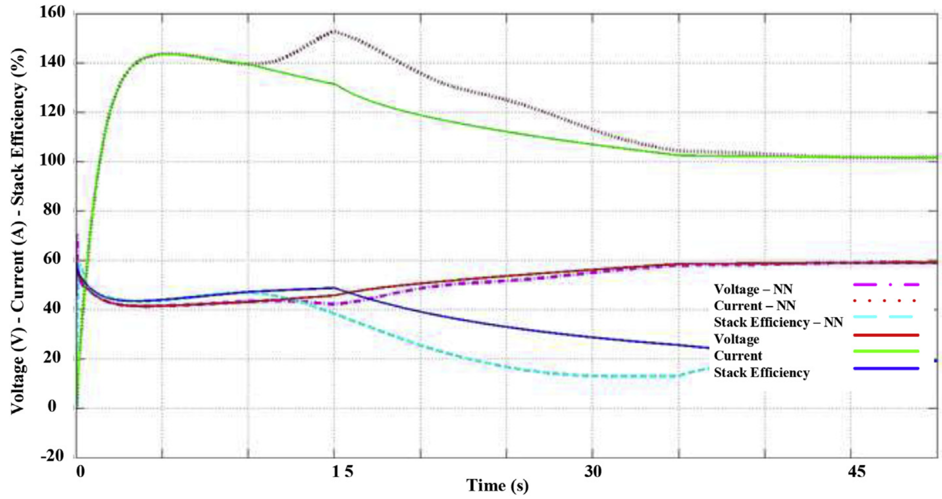


**Fig. 12.** Voltage, current and stack efficiency outputs of Model 2 for the varied inputs.

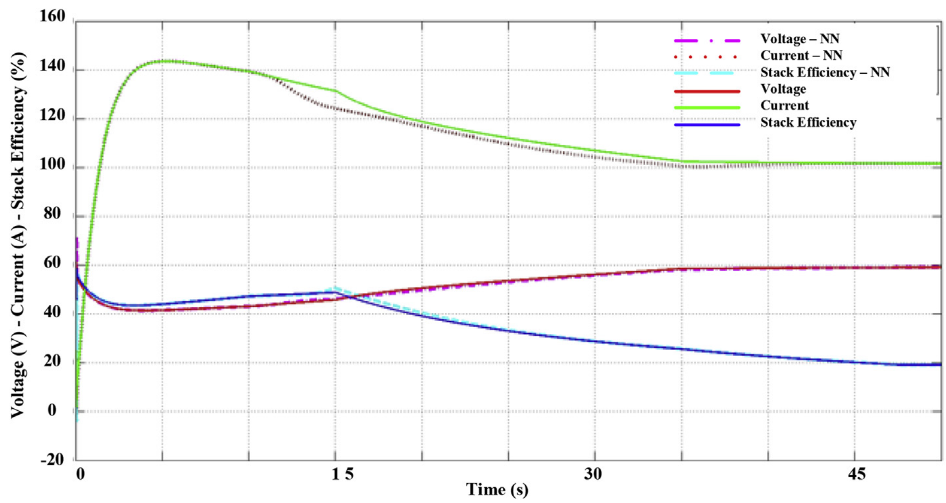


**Fig. 13.** Voltage, current and stack efficiency outputs of Model 3.

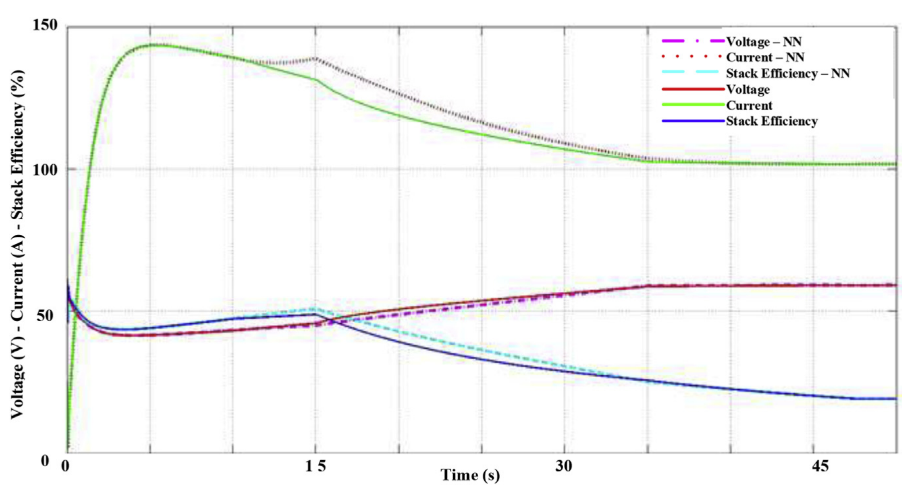


**Fig. 14.** Voltage, current and stack efficiency outputs of Model 4.

hidden layer numbers is investigated by using Case 6 as shown in Figs. 19–22. In Fig. 19, the fuel flow rate is increased to 150 L $m^{-1}$ between 10 and 20 s by a ramp function, the temperature rises with a constant slope up to 350 K within 35 s and the air flow rate remains constant after 33 s. Fig. 20 indicates the results for the inputs given in Fig. 19. The tracking capability of the ANN model is a

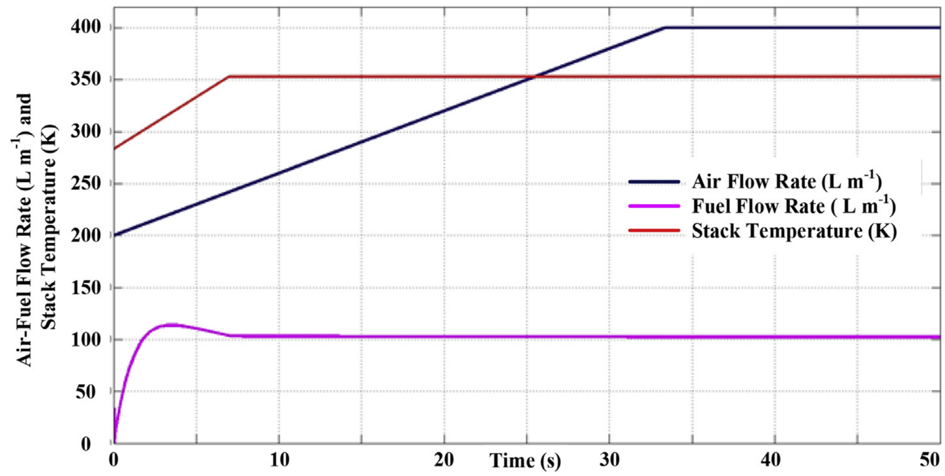


**Fig. 15.** Air flow rate, fuel flow rate and stack temperature inputs for Model 5.

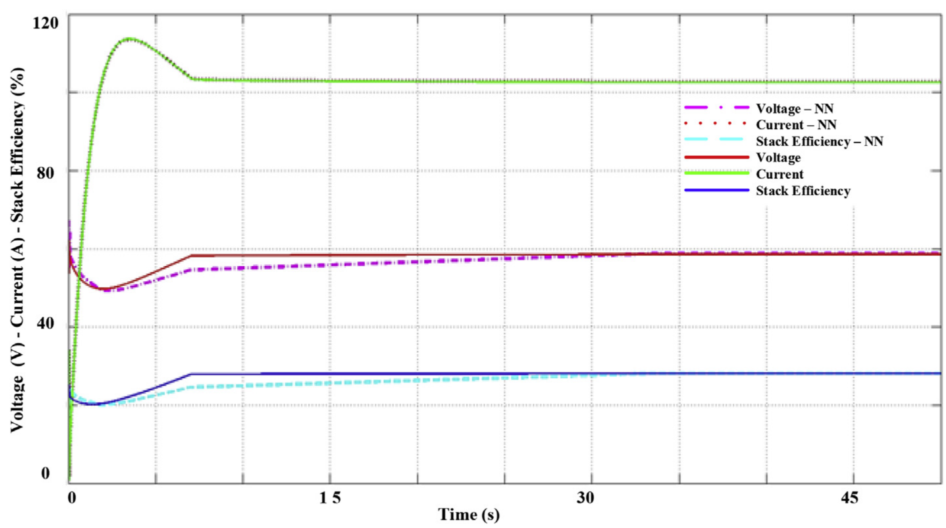


**Fig. 16.** Voltage, current and stack efficiency outputs of Model 5.

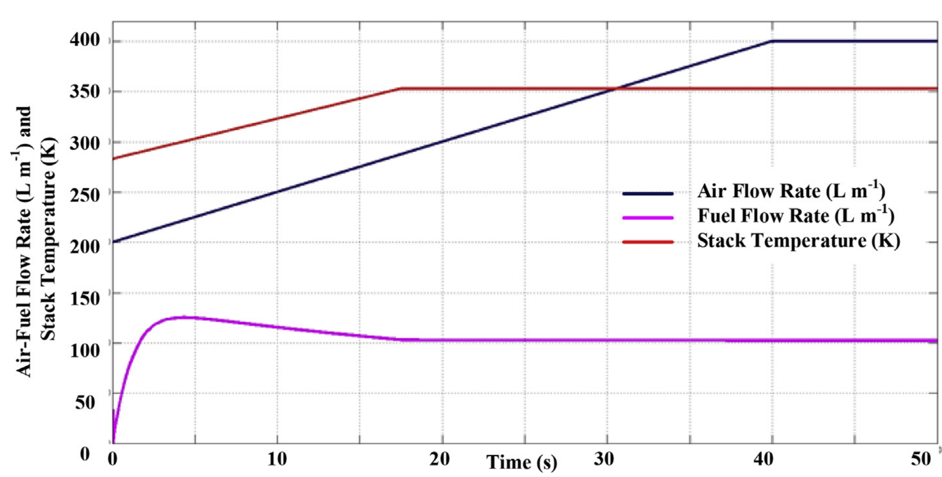


**Fig. 17.** Varied air flow rate, fuel flow rate and stack temperature inputs for Model 5.

slightly less than Case 5 for the first 25 s, however, after that ANN model follows the simulation results without any error. When different inputs are fed to Case 6 as seen in Fig. 21, there is a deviation in current output at 10 s caused by the introduction of a rump function for the fuel input. Being different from the previous fuel inputs, the fuel flow rate for Case 6 is increased drastically in

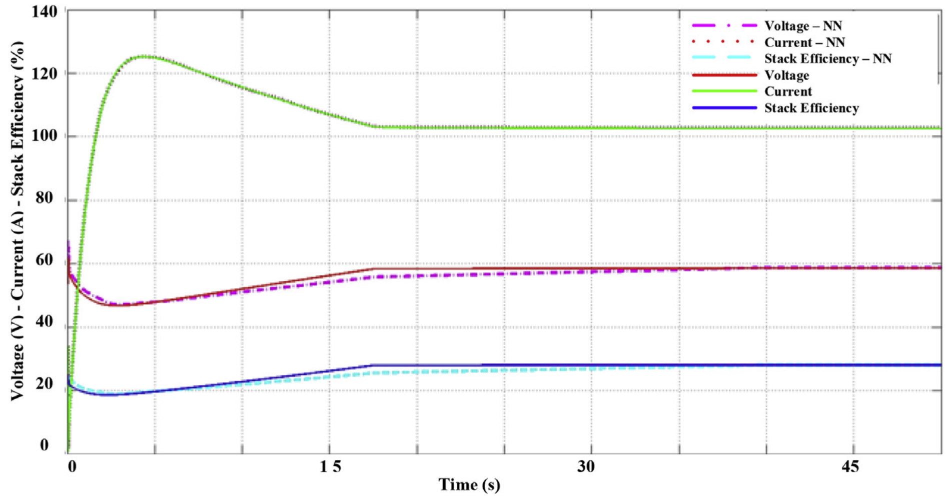


**Fig. 18.** Voltage, current and stack efficiency outputs of Model 5 for the varied inputs.

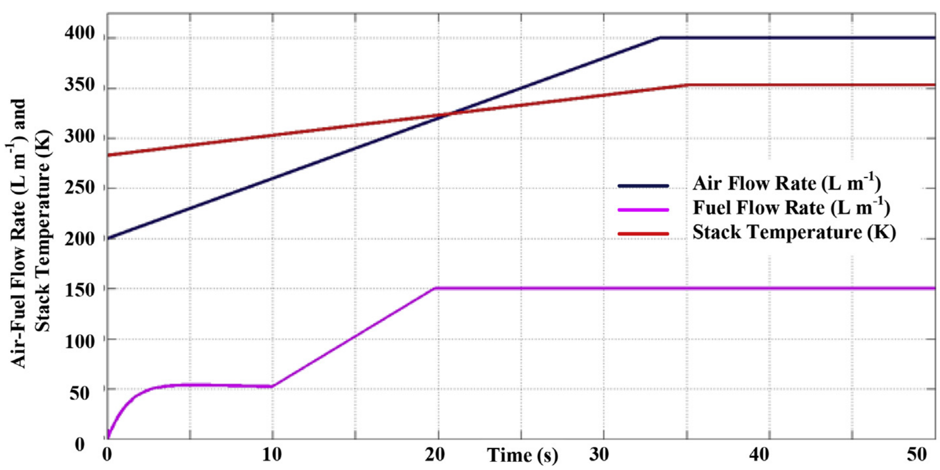


**Fig. 19.** Air flow rate, fuel flow rate and stack temperature inputs for Model 6.

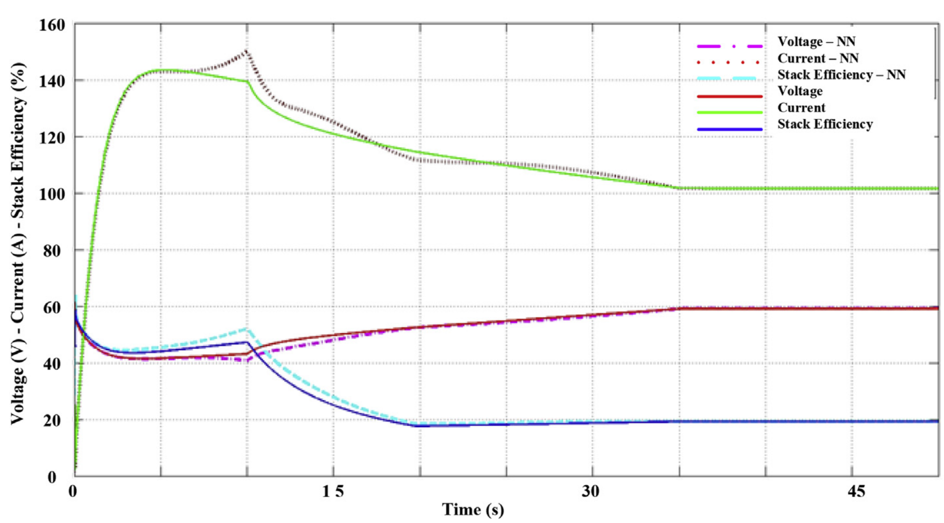


**Fig. 20.** Voltage, current and stack efficiency outputs of Model 6.

order to observe the dynamic response of the fuel cell for sudden changes. The slope of the rump function for fuel input is 10 in Fig. 19 whereas it is about 14 in Fig. 21. Therefore, the following characteristics of the ANN model decrease for a short period of time. However, it is recovered within 5 s and model starts to track simulation results with zero error as shown in Fig. 22.

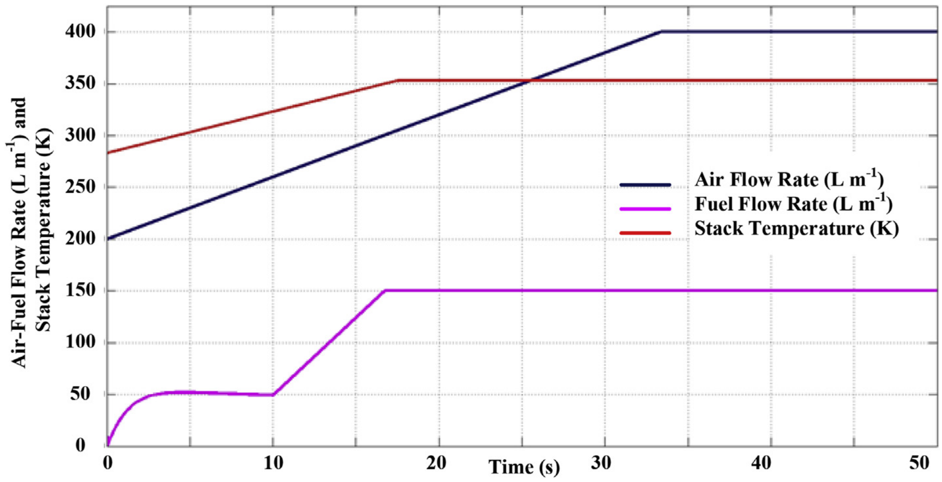


**Fig. 21.** Varied air flow rate, fuel flow rate and stack temperature inputs for Model 6.

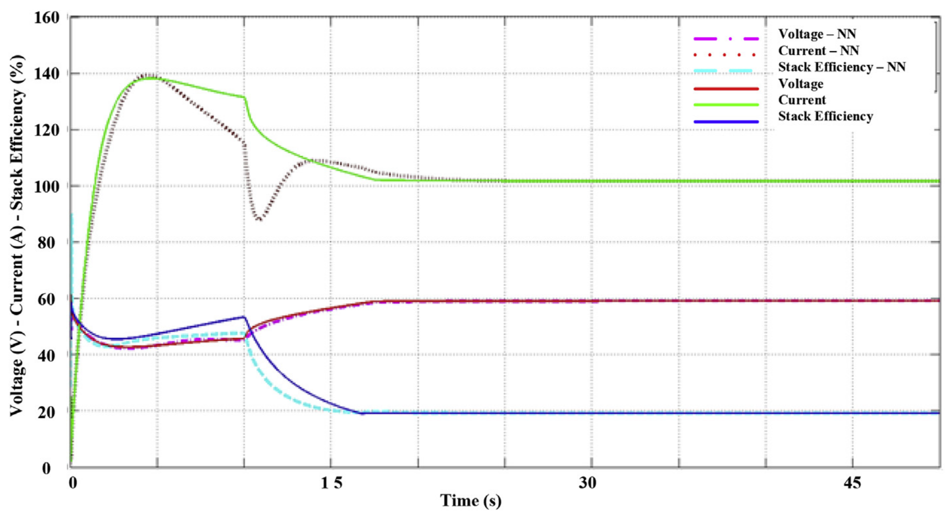


**Fig. 22.** Voltage, current and stack efficiency outputs of Model 6 for the varied inputs.

When compared with previous literature which utilized the neural network methodology for PEM fuel cells, the current results have a good match in terms of accuracy and reliability. In the study by Hatti and Tioursi [19], they were able to make estimates of the output of active power in control mode. They also implied that NN controller is rapid, accurate and robust, which indicates a good fit between the simulations and actual data. In their model, steady state is established after 18 s of feeding fuel, hydrogen and oxygen. In the present study, the steady state for most of the cases is satisfied below 30 s although there are a few cases close to 45 s. They obtained the best performance of $9.27219 \times 10^{-7}$ whereas it is $2.08 \times 10^{-5}$ in the current study for Case 3. The maximum difference between the models for power output was about 10% at 15 s in Ref. [19]. In this study, the maximum difference was observed for current outputs at 15 s about 13.3% for Case 2 and at 11 s about 25% for Case 6. It was shown in Ref. [15] that the FCPP with the embedded NN controller has a fast response to residential load changes and exhibits good load following capability. In Ref. [16], the maximum difference between NN model and the reference case was about 3% for active power outputs and 9% for hydrogen flow rate at 10 s. Transient response of the NN model over a short-time period and state space model response of a PEM fuel cell was comparatively shown in Ref. [36] and the maximum difference was found to be about 3%. The MSE for training and testing data in radial basis function model was obtained as 0.0011 and 0.00482, respectively in Ref. [18] whereas they are calculated as 0.00107 and 0.00229 for Cases 2 and 6, respectively in this study. Similarly, the maximum error between practical data and ANN data was calculated as about 6% for voltage output of the PEM fuel cell in Ref. [37] whereas it is about 5% for voltage output in this study for Case 5.

In this study, the results related to different type of training methods, number of samples and number of hidden layers are comparatively illustrated. If the number of samples are fixed and only training method is varied, Bayesian Regularization method yields better results. When number of samples are significantly increased by using Bayesian Regularization method, accumulated error of ANN increases slightly and prediction capability of ANN decreases. It is observed that increasing the number of samples does not necessarily mean better training of ANN. When number of hidden layers decreased to 10, ANN error is higher and tracking capability is lower. Training the ANN repeatedly gives better results in terms of prediction capability.

## 5. Conclusions

In this study, a comparative assessment of the PEM fuel cell model in MATLAB and artificial neural network model of PEM fuel cell model is conducted. The effects of hidden layers, training methods and number of samples on the performance of ANN model are investigated. Various simulation results are obtained in order to compare the outputs of PEM fuel cell model and ANN model. The present results show that the neural networks using back propagation method are effective for prediction of fuel cell output variables such as stack voltage, current and efficiency. If the ANN is built properly with correct input-output combination, network design, learning algorithms and error goal; it is shown that the capability of estimating the performance of a specific fuel cell in a short period with a reasonable accuracy is possible. Consequently, a neural network can be an alternative method to model a fuel cell especially for the predictions of input-output relations where physical models are not present. It is observed that obtaining similar performance with hybrid models, the ANN model requires to be trained with considerably higher data sets. The method of training and selection of number of hidden layers are significant for the ANN model prediction. However, increasing the number of samples may bring oversizing problems together with inaccuracies. The proposed ANN model and the fuel cell model are tested via simulated ramp changes in the stack voltage, current and efficiency. The stack efficiency varies between 20 and 60% for the selected cases. It is observed that rapid changes in the input variables can be recovered within a short time period, such as 10 s when the model is properly trained. The minimum error is obtained in voltage output predictions whereas the maximum error is obtained in current outputs. However, the steady state errors are eliminated. In conclusion, the results express a rapid response of the ANN model to variations of the load, and the efficiency of the proposed model by implying the load tracking capability of the fuel cell system and yielding good agreement with ANN predicted results.

## Acknowledgement

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## Nomenclature

| | |
|---|---|
| ANN | Artificial Neural Network |
| BP | Back-Propagation |
| BR | Bayesian Regularization |
| DC | Direct Current |
| $E^o$ | Standard Reversible Cell Potential (V) |
| F | Faraday's Constant |
| FC | Fuel Cell |
| I | Stack Current (A) |
| $i_L$ | Limiting Current (A) |
| $i_0$ | Electron Transfer Coefficient (A) |
| K | Kelvin |
| kW | Kilowatt |
| LCE | Levelized Cost of Energy |
| LM | Levenberg-Marquardt |
| MCFC | Molten Carbonate Fuel Cell |
| MSE | Mean Squared Error |
| MWh | Megawatt Hour |
| $N_o$ | Number of Cells in Stack |
| $n_a$ | Number of Electrons |
| PCU | Power Control Unit |
| PV | Photovoltaic |
| $R$ | Ohmic Resistance (Ω) |
| R | Regression |
| RBF | Radial Basis Function |
| SOFC | Solid Oxide Fuel Cell |
| T | Stack Temperature (K) |
| $U_f$ | Fuel utilization (%) |
| $V_o$ | Open Circuit Potential (V) |
| $V_{act}$ | Activation Losses (V) |
| $V_{con}$ | Concentration Losses (V) |
| $x_i$ | Mole Fraction of Species |

*Subscripts and superscripts*

| | |
|---|---|
| act | Activation |
| con | Concentration |
| $H_2$ | Hydrogen |
| $O_2$ | Oxygen |

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