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MULTI INPUT SINGLE OUTPUT NEURAL NETWORK MODELLING AND IDENTIFICATION OF PROTON EXCHANGE MEMBRANE FUEL CELL

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Abstract

Due to the nonlinear and time variant characteristics of Proton Exchange Membrane Fuel Cell (PEMFC), its control is complicated. Thus, a suitable model is needed for PEMFC to gain higher performance stabilization and control. In this paper, the prediction of complicated behaviour of PEMFC is investigated using Artificial Neural Networks (ANN). The averaged cell voltage is regarded as the output; the current density and the cell temperature are considered as the inputs of neural networks. The experimental data are utilized for training and testing the networks. Multilayer perceptron (MLP) with one and two hidden layers and Radial Basis Function (RBF) networks are built, optimized, and tested in MATLAB environment. In order to study the efficiency of the neural network model, a comparison of the results is made through the Support Vector Machine (SVM) model. It is shown that neural model has better and more accurate prediction results than the SVM model of fuel cell, especially in low current region of fuel cell operation. In addition, the performance prediction of PEM fuel cell neural models with noisy data is carried out in order to check the effect of noise on the optimal structure of networks as well as the robustness of neural models.

Keywords: Proton Exchange Membrane Fuel Cell, Neural network, Identification.

1. Introduction

High demand for energy as well as environmental problems due to the development of human society makes the tendency to consume energy resources with little pollution and higher production efficiency. During recent decades, considerable attention has been paid to fuel cells among the renewable energies. PEM fuel cell is considered as a suitable resource to produce electrical energy among various kinds of fuel cells for its high efficiency, quick start up, high current density, very low intrusion to the environment, light weight, as well as low operational temperature.

Nonlinear and time variant characteristics of PEMFC degrade the control performance of conventional controllers. A suitable mathematical model of the system is needed for precise controlling of the process. Several mathematical models have been proposed for a better understanding of the characteristics and evaluation of the performance of PEM fuel cell by numerous authors [1]-[10]. Most of the models are based on the knowledge of electrochemistry, thermodynamics, and fluid mechanics and need a number of PEM parameters and approximate. Hence, they are not appropriate for the desired control of a fuel cell system.

Artificial neural networks have proved themselves as powerful tools for modelling of unknown systems. A trained neural network with sufficient neurons in hidden layers can learn the relationships between its input and output signals with high accuracy during a process known as learning algorithm.

In recent years, the efficient techniques based on artificial neural network (ANN) have attracted much attention for fuel cell systems. So far, many investigations based on neural networks for modeling and control of PEM fuel cell has been developed in the previous literature. Saengrung et al. in [11] have investigated performance prediction of a commercial proton exchange membrane fuel cell system by using two artificial neural networks including the back-propagation (BP) and radial basis function (RBF) networks which the air flow and stack temperature are as the inputs and stack voltage and stack current are as the outputs. Rouss and Charon in [12] have proposed a method based on a MIMO multi-layer perceptron (MLP) neural network combined with a time regression input vector approach for the mechanical nonlinear behaviour of a proton exchange membrane (PEM) fuel cell system. Paulo et al [13] to control the output voltage of a proton exchange membrane fuel cell by parametric cerebellar model articulation controller (P-CMAC) have proposed a new approach to design neural optimal control systems. Lobato et al in [14] have designed three types of neural networks, that have as common characteristic the supervised learning control (Multilayer Perceptron, Generalized Feedforward Network and Jordan and Elman Network), to model the performance of a polybenzimidazole-polymer electrolyte membrane fuel cells operating upon a temperature range of 100–175 ◦C. Shaoduan et al. [15] have incorporated the effect of Pt loading in the ANN model of Proton exchange membrane fuel cells that can be very helpful when the effect of Pt loading is needed for further analysis of a fuel cell system. Jemei et al. [16] have developed a proton exchange membrane fuel cell (PEMFC) system neural network model which has four input nodes including stack current, stack temperature, hydrogen flow, and oxygen flow and a linear output neuron to estimate the voltage. For the power tracking of fuel cell a model-predictive control is used in Golbert’s work [17]. Hatti et al. [18] have modelled the static behaviour of the proton exchange membrane fuel cell is using artificial neural networks. A practical method of estimation for the internal-resistance of polymer electrolyte membrane fuel cell (PEMFC) stack have adopted based on radial basis function (RBF) neural networks by Wei et al. [19]. Hatti et al. [20] have proposed Quasi-Newton neural network model which considering the cell operational temperature as inputs, the cell voltage and current density as the outputs. Hatti and Tioursi [21] have obtained a dynamic neural network control model by introducing a delay line in the input of the neural network to control of a PEM fuel cell system process. The application of non-linear predictive control with neural networks to regulate the cell voltage, acting on the hydrogen pressure, trying to reduce the variation of the input control variable have investigated by Cirrincione et al in [22].

Fuel cell is an electrochemical device, which is considered as a multi-input and multi-output (MIMO) system that is hard to model by conventional methods. Herein, PEMFC is regarded as a two input and one output system in which the current density and cell temperature are chosen as the inputs and the averaged cell voltage is selected as the output of the neural network. In this paper, the RBF network and the MLP network with one and two hidden layers are considered to identify the PEMFC. These networks are made, optimized, and tested with experimental data obtained from a Ballard MK5-E [23]. In order to study the efficiency of the neural network model, the acquired results are compared with the SVM model of PEMFC. In continue, the performance prediction of PEM fuel cell neural models with noisy data is carried out in order to check the effect of noise on the optimal structure of networks as well as the robustness of neural models.

This paper is arranged as follows: In Section 2, the PEMFC is studied concisely. Section 3 is briefly concerned with MLP and RBF neural network theory. The modelling of PEMFC by means of neural network and preparing the network for training are shown in detail in Section 4. In section 5, simulation results of neural models are indicated. The effect of noise is investigated in section 6. Finally, conclusion is stated in Section 7.

2. Proton Exchange Membrane Fuel Cell

Fuel cell is a new device for distributed power generations, which can produce electrical energy continuously as long as hydrogen and oxygen are fed to it.

In recent years, the PEM fuel cell is being widely developed for using in vehicles and portable applications and is seen as the main fuel cell candidate technology for light-duty transportation applications [24]. The schematic of a PEMFC is shown in Fig. 1.

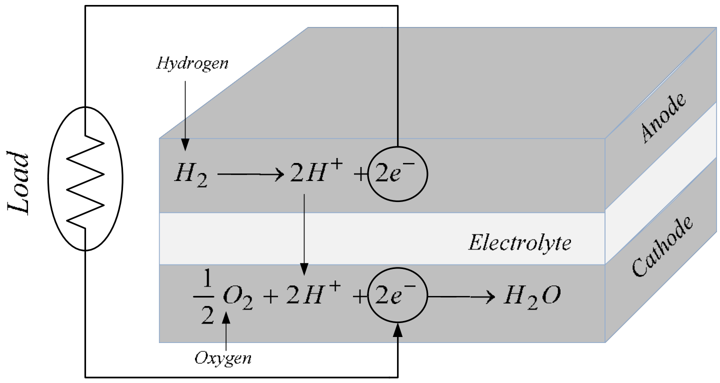

Fig. 1. Schematic of a Proton Exchange Membrane Fuel Cell

In normal operation of a PEMFC, the hydrogen gas is fed to the anode side and oxygen, usually from the air, is fed to the cathode side. In the anode and at the presence of platinum, which is usually used as catalyst, the hydrogen gas releases electrons and H^+ ions (or protons). The polymer electrolyte only allows the protons to pass through it, and not electrons. Via the external circuit, the electrons move from anode to the cathode and accordingly an electrical current flows through the circuit. At the cathode, oxygen reacts with the electrons taken from the external circuit and the protons from the polymer electrolyte and produces water. Total reaction, which is occurred in the fuel cell, is shown by:

$$H_2 + \frac{1}{2}O_2 \xrightarrow{pt} H_2O + \text{electrical power} + \text{thermal power} \tag{1}$$

The produced voltage by a single fuel cell is very small about $0.7\,v$. This means that in order to use in practical applications, many fuel cells have to be connected in series. Such connection of fuel cells in series is known as a stack.

Among empirical PEM fuel cell models described in the literature, Amphlett et al. [25] and Kim et al. [26] introduce an influential model, which is widely used in analytical problems. Based on these models, the cell voltage is defined by the following expression:

$$V_{cell} = E_{nernst} - V_{act} - V_{ohmic} - V_{con} \tag{2}$$

where E_{nernst} is the open cell voltage and shows reversible voltage of the cell. V_{act}, V_{ohmic} and V_{con} are activation, ohmic, and concentration voltage drops, respectively. More details are entirely discussed in literature. Eq. (2) provides a good representation of PEMFC behaviour, but the coefficients of this model are extremely related to operating conditions such as cell temperature, inlet pressures, and flow rates and so on. Therefore, PEMFC parameters are time varying and it is very difficult to keep them unchanged during its operation. Hence, the model will give incorrect results with constant parameters. A novel modelling approach, such as neural network in this paper, is required to indicate a better control performance.

3. Neural network theory

A neural network is a parallel-distributed processor with important virtue of the ability to learn from input data by using of a learning algorithm. The ANN is made up of an interconnection simple processing unit, known as neurons. Neurons can be either linear or nonlinear. Usually, situated neurons in the hidden layer are selected nonlinear while the neurons in the output layer are chosen linear. In recent researches, neural networks have been considered as potent tools for modelling of complicated and unknown systems. Neural networks can adapt themselves with variations in the environment conditions and learn the characteristics of their input signals.

Multilayer perceptron and radial basis function networks are two different kinds of neural networks, which are commonly used in system predictions. MLP network is a feed forward neural network that is successfully utilized for identification of systems in many branches of science. MLP is made up of one or more hidden layers. It employs Back Propagation algorithm (BP) for training the network. In Back-propagation algorithm, the layer weights and biases are updated until the stopping criterion is satisfied [27]. RBF network is one of the most powerful neural networks, which is used in function estimation problems. In comparison with the MLP network that can have multiple hidden layers, the RBF network is composed of three layers. The input layer for supplying the input signals to the network, the middle layer, which contains RBF functions, and the output layer, which is a linear composition of middle layer outputs for producing the final output.

4. Modeling of PEMFC by neural networks

The performance of PEMFC is affected by operating variables such as current density I, cell temperature T, oxygen pressure P_{O2}, oxygen flow rate q_{O2}, hydrogen pressure P_{H2}, hydrogen flow rate q_{H2}, membrane humidity l, and many other factors which influence the terminal voltage of a fuel cell. Therefore, the output voltage is defined by:

$$U = f\left(I, T, P_{O2}, q_{O2}, P_{H2}, q_{H2}, l, ...\right) \tag{3}$$

A model regarding all of cell parameters has not been introduced, yet. Our neural models are no exception. In this experiment, the current density, that can change with varying loads, and the cell temperature —a parameter that changes during the operation— are taken as variables while the other parameters are held constant. Accordingly, the Eq. (3) is simplified and expressed by:

$$U = f\left(I, T\right) \tag{4}$$

Thus, a neural network model with two inputs and one output is formed. The current density and cell temperature are selected as the inputs and averaged cell voltage is chosen as the output signal of network. Herein, the studied PEMFC is a BALLARD 5KW MK5-E with 36 cells and 232 cm^2 active area for each cell. Air and hydrogen pressures are both regulated to 3 atm. The studied PEMFC has been introduced in Ref [23]. The fuel cell system is operated in different conditions and experimental data is acquired to be utilized in neural network. The obtained data at 24°^{C}, 31°^{C}, 39°^{C}, 56°^{C}, and 72°^{C} in various current densities are used for training and testing the NN model. In our investigation among the collected data, the data at 56°^{C} is selected for testing the network and other collected data are used for training the NN. For training the network, the range of input data must be specified. The range of current density is from zero to 700 mA/cm^2 and cell temperature is in the range of 20°^{C} to 80°^{C}. Normalized data increase the training speed. Thus, by using the Eq. (5), all the raw data including averaged cell voltage, current density and temperature can be normalized to have a range between 0 and 1.

$$X_{normalized} = \frac{X_{raw} - X_{\min}}{X_{\max} - X_{\min}} \tag{5}$$

Fig. 2 shows the experimental data with which the averaged cell voltage is defined according to current density and temperature.

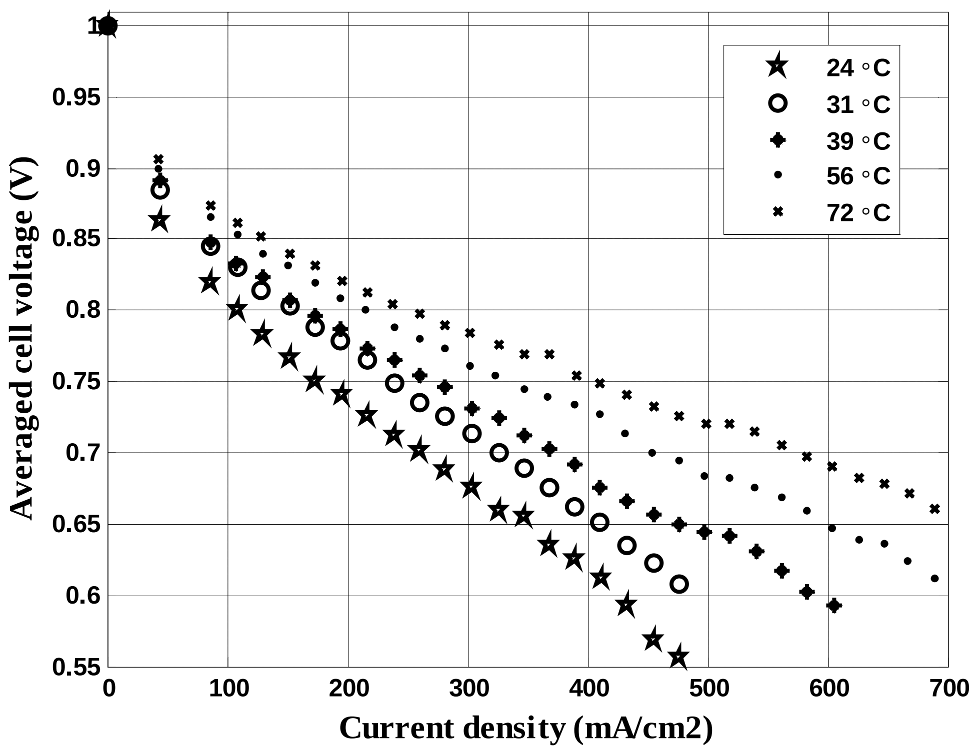

Fig. 2. Averaged cell voltage according to current density and cell temperature of 5KW Ballard fuel cell

5. Simulation Results

5.1. Performance prediction of MLP model

A typical MLP network with two hidden layers is shown in Fig. 3.

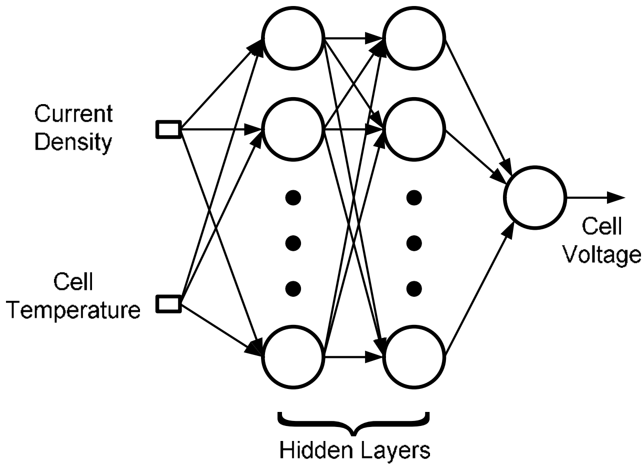

Fig. 3. MLP network with two hidden layers for performance prediction

At first, performance prediction is performed by MLP model with one hidden layer. For the best performance of MLP network, the number of epochs and neurons in the hidden layer must be optimized. By trial and error method, the number of neurons is changed from 1 to 10 and in each case the optimal number of epochs is found. To find the optimum number of epochs, the Mean Square Error (MSE) curve for training and testing data set is plotted. For an increasing number of epochs, the MSE of training data set decreases monotonously. In contrast, the testing data set curve decreases monotonously to a minimum and then, it starts to increase as the training continues. This heuristic approach suggests that the minimum point on the testing curve be used as a suitable criterion for training stop [27]. Trial and error results are shown in Table 1. As the results show, 3 neurons with 25 epochs have the best performance so that the MSE values for both the training and testing data sets are less than other cases and acceptable. Therefore, are selected as optimal values.

In MLP network, the hidden neuron activation functions are hyperbolic tangent sigmoid and the output neuron is linear.

Table 1. Trial And Error Results For Finding The Optimal Structure Of Mlp Network With One Hidden Layer

#Neurons	Optimum epochs	MSE- training	MSE- test
1	26	0.0052079	0.0024434
2	31	0.0013635	0.0024647
3	25	0.00060961	0.0014725
4	12	0.00070443	0.0025523
5	15	0.000462	0.012915
6	39	0.00013958	0.0164
7	7	0.00112	0.057462
8	6	0.00089131	0.085045
9	7	0.000709	0.12658
10	3	0.012614	0.2175

The prediction of averaged cell voltage for testing data set is represented in Fig. 4.

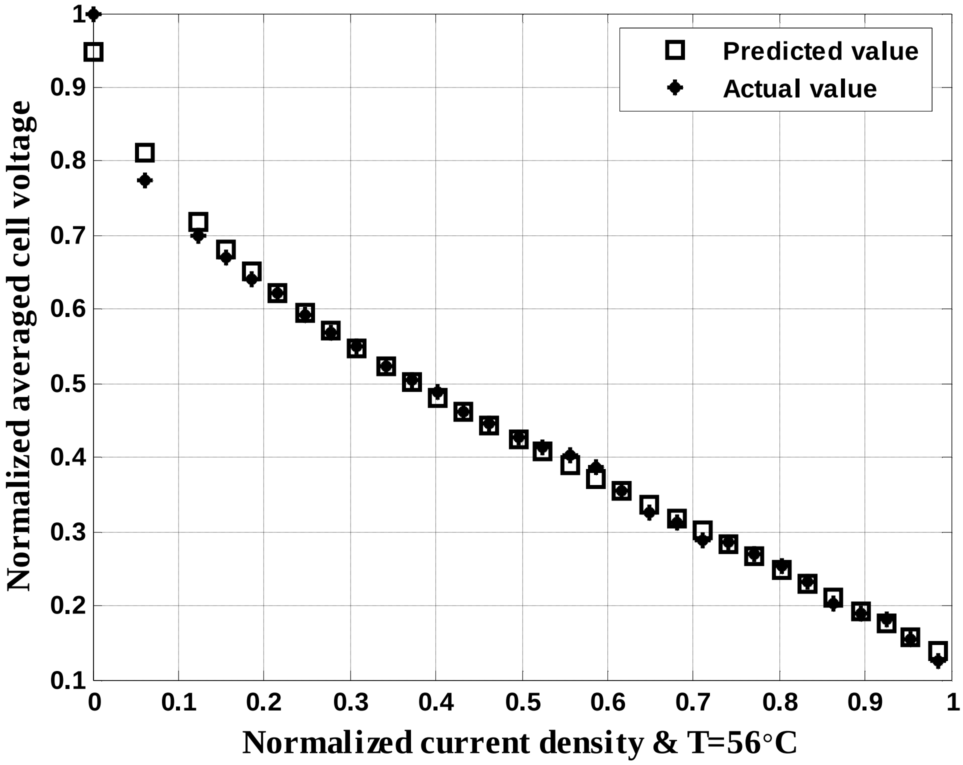

Fig. 4. Performance prediction of MLP with one hidden layer for testing data

As Fig.4 shows, the optimized MLP model performs very well and the predicted values are very close to the actual values.

Secondly, the MLP neural network with two hidden layers is considered to identify the PEMFC model. Consequently, the number of neurons in the first hidden layer is fixed at 3 and the number of neurons in the second hidden layer is determined by trial and error method. As Table 2 indicates, 2 neurons in the second hidden layer with 25 epochs have the best performance and are selected as optimal values. The prediction of averaged cell voltage for testing data set is shown in Fig. 5.

Table 2. Trial And Error Results For Finding The Optimal Structure Of Mlp Network With Two Hidden Layers

#Neurons	Opt-epochs	MSE-raining	MSE- test
1	18	0.0057941	0.0086884
2	25	0.0012605	0.003232
3	25	0.0025194	0.0079329
4	18	0.0018195	0.010877
5	25	2.31e-03	0.007752

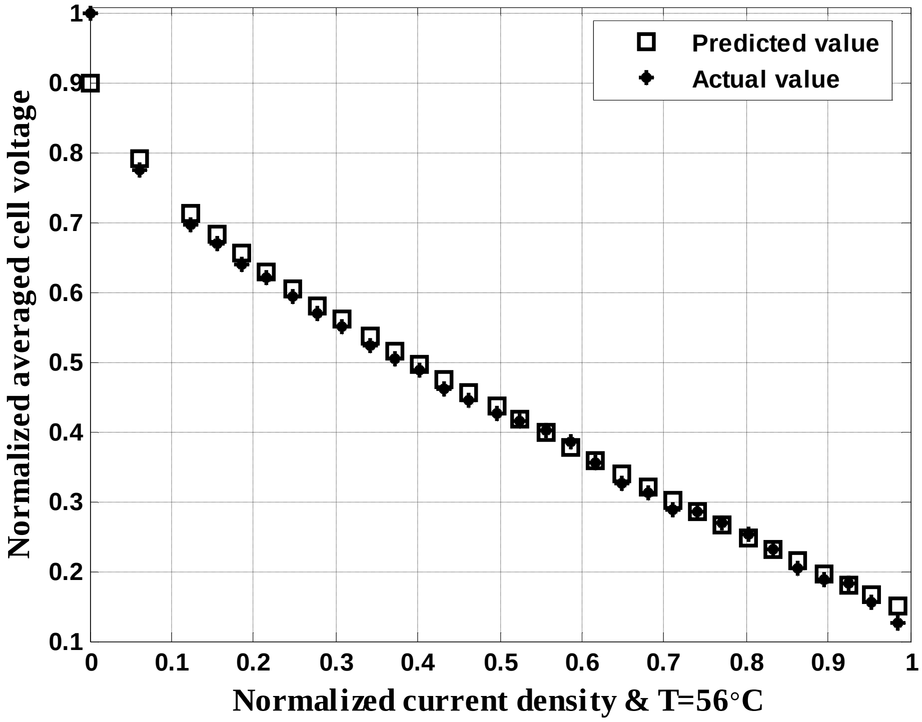

Fig. 5. Performance prediction of MLP with two hidden layers for testing data

The results indicate the satisfactory predictions for both of the MLP networks at the whole operating range. The MLP with one hidden layer is suggested rather than MLP with two hidden layers due to its simple structure and better performance in terms of MSE. It is found that using of more than one hidden layer do not improve the performance prediction of the neural network.

5.2. Performance prediction of RBF model

Fig. 6 shows the configuration of the RBF neural network which is solely composed of one hidden layer. In this network, the hidden neuron activation functions are Gaussian and the output neuron is linear.

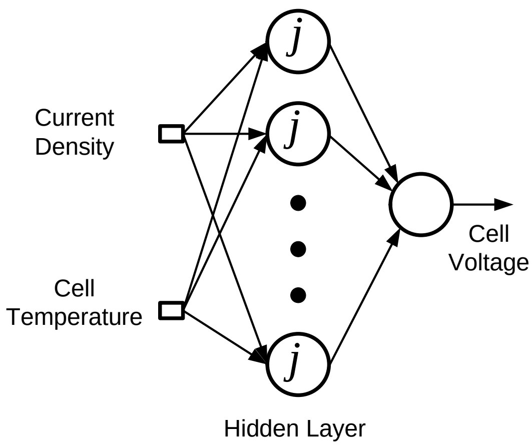

Fig. 6. RBF network for performance prediction

By trial and error method, the optimal number neurons at the hidden layer are found at 10. Fig. 7 indicates the predicted data at $56\,°C$, which were selected as testing data set.

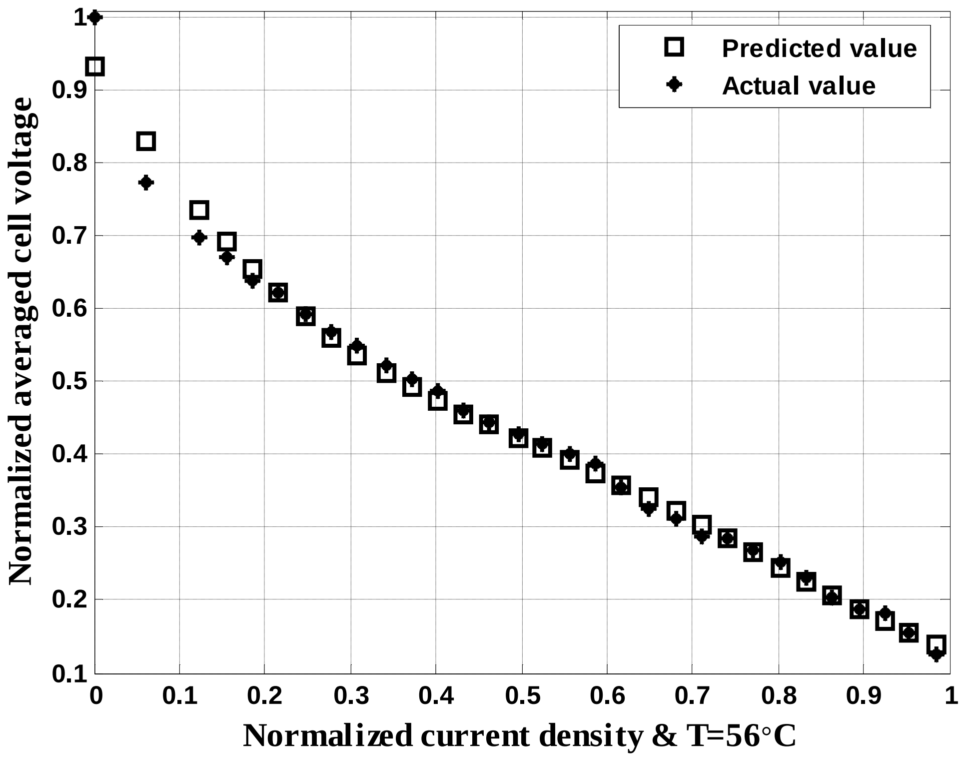

Fig.7. Performance prediction of RBF network for testing data

The obtained results represent that in this case the RBF model do not act better than the MLP networks in performance prediction of averaged cell voltage. The MSE for training and testing data in RBF model is obtained at 0.0011 and 0.00482, respectively. In this case, among the built and optimized neural network models, the MLP model with one hidden layer acts better than others in terms of mean square error. Moreover, it uses fewer numbers of neurons in the hidden layer; therefore, it is suggested.

In order to study the efficiency of the neural network model, the support vector machine model for PEMFC—investigated in Ref [28]—is also simulated and the obtained result from the SVM model is compared with the best predictions of the investigated neural networks, i.e. MLP with one hidden layer. Fig. 8 shows the obtained results.

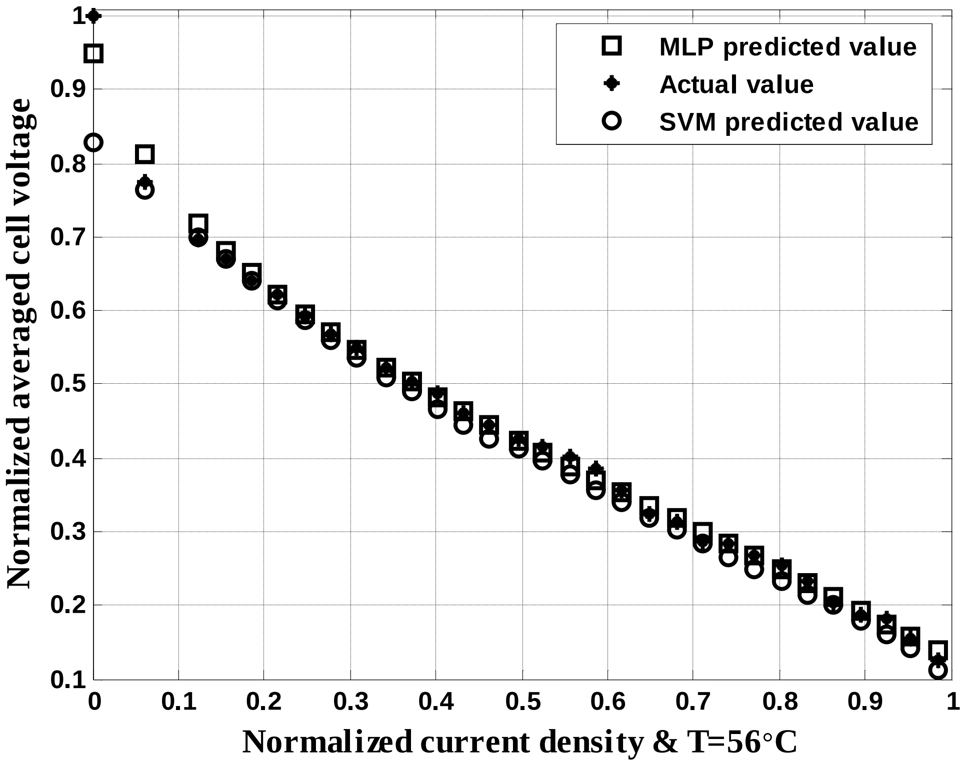

Fig. 8. The comparison between the MLP with one hidden layer and SVM models

The neural network model performs a better identification of the fuel cell averaged voltage rather than the SVM model especially in beginning of curve. As Ref [28] represents, although the SVM model has satisfactory results, but a considerable error exists between actual values and predicted values in the beginning of curve. For obviation of this problem, the SVM model needs more data points for training at the beginning of curve. If several data points are found and the SVM is trained again, the predicted values in the beginning of curve can be improved [28]. Neural network models have better performance at the beginning of curve as compared to SVM model, and this feature shows the ability of neural networks in performance predictions.

6. Noise effect

In the following section, the performance prediction of PEM fuel cell neural models with noisy data is carried out in order to check the effect of noise on the optimal structure of networks as well as the robustness of neural models. The noisy data is derived by adding the normal noise to the averaged cell voltage. Therefore, the noisy averaged cell voltage can be obtained by:

$$V_{noisy} = V_{noise-free}(1 + level \times rand) \quad (6)$$

where $V_{noise-free}$ is the original noise free averaged cell voltage, V_{noisy} is the averaged cell voltage with noise, $rand$ is a random number between -1 and 1, and level is the relative percentage of error to be added. Here, the MLP with one hidden layer and RBF networks are studied with the noise level at 1%.

The MLP network with one hidden layer is trained again with noisy data and optimal structure is found. Four neurones in hidden layer with 29 epochs are obtained for optimal structure. The optimal structure of neural model changes when noise is applied to the system. Fig. 9 represents the performance prediction of MLP model with noisy data.

The RBF network with one hidden layer is also trained again with noisy data and optimal structure is found. Optimal structure for hidden neurones in RBF network is acquired at 11 which involve one neuron more than free noise RBF network. Fig. 10 shows the performance prediction of RBF model with noisy data.

As it can be seen, if there is an additive noise, the predicted values by MLP and RBF models are close to the noisy values. In the presence of noise (level 1%) the performance prediction precision is acceptable in engineering.

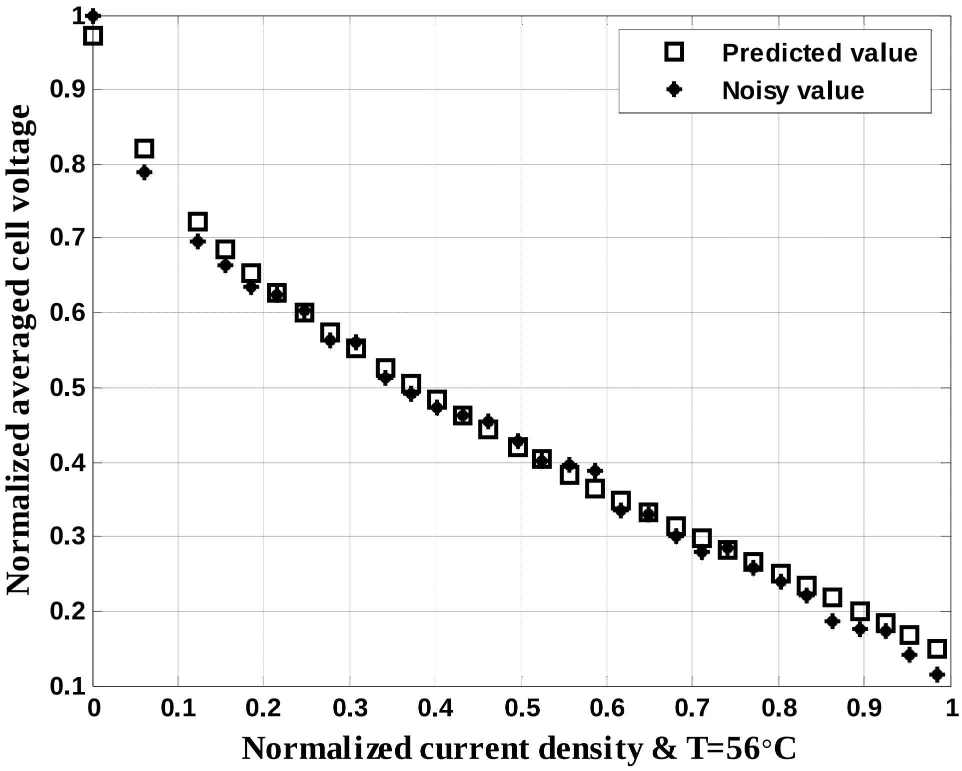

Fig. 9. Performance prediction of MLP with one hidden layer for testing noisy data

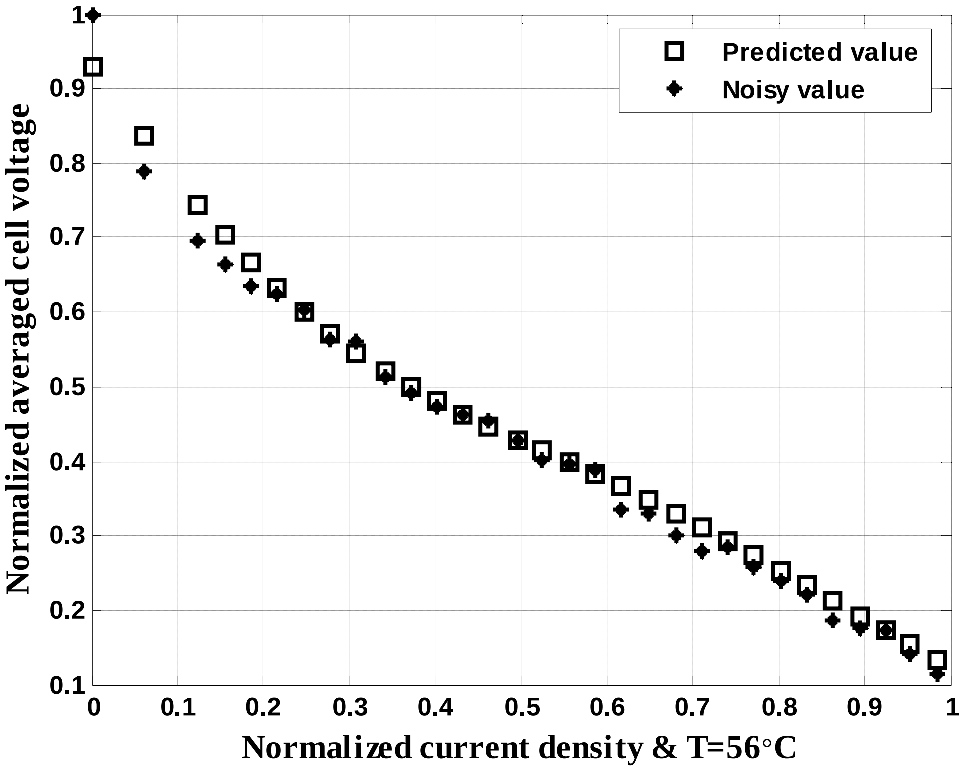

Fig.10. Performance prediction of RBF network for testing noisy data

7. Conclusion

In this paper, the performance prediction of a Ballard MK5- E PEMFC is investigated using the MLP and RBF networks. Herein, PEMFC is regarded as a two input and one output system in which the current density and cell temperature are chosen as the inputs and the averaged cell voltage is selected as the output of the neural networks and is simulated in Matlab environment. The obtained results show that optimized neural network models can successfully predict the averaged cell voltage and they are more accurate than other modelling solutions such as SVM model especially in low current region of fuel cell operation. In addition, the performance prediction of PEM fuel cell neural models with noisy data is carried out in order to check the effect of noise on the optimal structure of networks as well as the robustness of neural models. The results show that with noisy data the optimal structure change and neural models have satisfactory precision when are faced with noise.

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Nomenclature

H_2	Hydrogen gas
O_2	Oxygen gas
pt	Platinum
H_2O	Water
V_{cell}	Cell voltage (V)
E_{nernst}	Reversible voltage (V)
V_{act}	Activation voltage drop (V)
V_{ohmic}	Ohmic voltage drop (V)
V_{con}	Concentration voltage drop (V)
U	Average voltage of cell (V)
I	Current density (mA/ cm^2)
T	Cell temperature ($°C$)
P_{O2}	Oxygen pressure (atm)
q_{O2}	Oxygen flow rate (slpm)
P_{H2}	Hydrogen pressure (atm)
q_{H2}	Hydrogen flow rate (slpm)
l	Membrane humidity
$X_{normalized}$	Normalized data
X_{raw}	Raw data
$X_{\min}$	Minimum of data
$X_{\max}$	Maximum of data
j	Gaussian function
V_{noisy}	Averaged cell voltage with noise
$V_{noise-free}$	Original noise free averaged cell voltage
$level$	Random number between -1 and 1
$rand$	Relative percentage of error

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