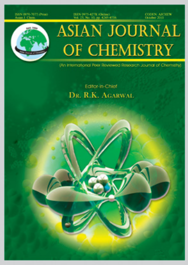
Asian Journal of Chemistry; Vol. 24, No. 11 (2012), 5413-5414

ASIAN JOURNAL OF CHEMISTRY

www.asianjournalofchemistry.co.in



NOTE

Prediction of Direct Methanol Fuel Cell Using Artificial Neural Network

HASAN SHARIFI PAJAEI[1], SAEID ABBASIAN[1] and BAHMAN MEHDIZADEH[2,*]

[1]Babol Noshirvani University of Technology, Babol, Iran
[2]Young Researchers Club, Chalus Branch, Islamic Azad University, Chalus, Iran

*Corresponding author: E-mail: ba.mehdizadeh@yahoo.com

(*Received*: 27 October 2011; *Accepted*: 21 June 2012) AJC-11655

An artificial neural network has been applied for performance prediction of direct methanol fuel cell. In order to optimization of neuron number in hidden layer, average relative deviation of neural network *versus* number of neurons has been plotted. Results showed 5-6-2 is the best topology of the neural network. Present study showed the proposed model has an average relative deviation about 2.95 % and 3.4 % respectively for training and testing subset.

Key Words: Direct methanol fuel cell, Artificial neural network, Performance prediction.

Nowadays, development of the hydrogen fuel cell, as a result of the shortage of energy resources and the greenhouse effect on earth, has attracted people's attention. The fuel cell does not need a time-consuming charging process and the emissions of the fuel cell are harmless to the environment. Thus the fuel cells can be used in power supplies for vehicles, uninterrupted power systems, notebooks and mobile phones[1]. A direct methanol fuel cell (DMFC) is an important electrochemical energy conversion device that converts chemical energy of liquid methanol into electrical energy directly[2]. Also direct methanol fuel cell is one of the most attractive power sources for wide applications from vehicles to portable uses, due to the simplicity of the system and the adaptability of methanol[3].

Fuel cell modeling has received much attention over the last decade. Different types of approaches are available in literature[4,5].

In an attempt to better understanding of the phenomena occurring within the cell, analytical models are an efficient tool to investigate the effect of basic variables on fuel cell performance. Also engineers can predict the fuel cell performance as a function of different operating conditions (such as pressure, temperature or fuel concentration) using simple empirical equations by means of semi-empirical models[5].

Because of non-linear nature of fuel cells, artificial neural network method may be considered as an alternative tool for prediction of fuel cell performance. Wang *et al.*[6] used artificial neural network for modeling of a 5-cell direct methanol fuel cell, Ou and Achenie[7] applied artificial neural network for PEM fuel cells. Ramirez *et al.*[8] used artificial neural network for simulation of high power fuel cell. The neural network has also been used for performance prediction of a proton exchange membrane fuel cell has by Vural *et al.*[9].

In this work, a feed-forward artificial neural network with Levenberg-Marquardt training algorithm has been applied in order to investigate its capability in performance prediction of direct methanol fuel cell.

Artificial neural network: As mentioned before neurons are main building block of neural networks. In an artificial neural network a neuron sums the weighted inputs from several connections and then output of neurons are produced by applying transfer function to the sum. There are many transfer function but common transfer function is sigmoid and we used this transfer function. Sigmoid function can be expressed by following equation:

$$\theta_j = \frac{1}{1+e^{-\Psi j}} \quad (1)$$

In eqn. 1, θ_j is sum of weighted inputs to each neuron and Ψ_j is output of each neuron and can be calculated from eqn. 2.

$$\Psi_j = \left(\sum_{i=1}^{n} w_{ij}.\theta_i\right) + b_j \quad (2)$$

In eqn. 2 w_{ij} denotes connection between node j of interlayer l to node i of interlayer l-1, b_j is a bias term and n is number of neuron in each layer. In any interlayer l and neuron j input values integrate and generate Ψ_j.

In order to minimize the difference between experimental data and calculated of neural network, mentioned process repeats for the total number of training data. After training, validation of neural network can be done by testing data.

Numerous types of the artificial neural networks exist such as multi-layer perceptron, radial basis function (RBF) networks and recurrent neural networks. The type of network used in this work is the multi-layer perceptron network. Multi-layer perceptron networks are one of the most popular and successful neural network architectures, which are suited to a wide range of applications such as prediction and process modeling.

Preparation of dataset: After collecting a large number of data sets for various operating parameters of a direct methanol fuel cell[10], cell operating temperature, methanol concentration, cathode humidification temperature, methanol flow rate and air flow rate have been devoted to the network as inputs. In this work, all data is divided into three parts [training subset (60 % of all data), validation subset (10 % of all data) and testing subset (30 % of all data)]. To prevent larger number from overriding smaller number; all data is normalized. Normalization can be done by several equations. In present work, data is scaled between [0.1-0.9] by means of eqn. 3.

$$(\text{Scaled})_{\text{value}} = \frac{(\text{Actual})_{\text{value}} - \min_{(\text{actual value})}}{\text{Max}_{(\text{actual value})} - \min_{(\text{actual value}}} \times 0.8 + 0.1 \quad (3)$$

Artificial neural networks modeling: Programming, validation, training and testing of the artificial neural networks model was carried out by MATLAB 7.7.0. All the programs were run on a Pentium IV (CPU 2.7 GHz and 2GB RAM) personal computer with windows XP operating system.

For determination of optimized values of weights and biases some processes need to be done. These steps are expressed in following paragraphs.

(1) Data need to be divided into three parts [training subset (60 % of all data), validation subset (10 % of all data) and testing subset (30 % of all data)]; (2) Data need to be normalized (by eqn.3); (3) Number of neurons in hidden layer need to be optimized; (4) Some other parameters for training procedure of neural network need to be selected by user.

In this work a three layer feed forward neural network has been used for performance prediction of direct methanol fuel cell. All parameters of neural network are determined by trial and error procedure. The most common transfer function is sigmoid function. In this work, we used sigmoid function for transfer function in hidden layer and purelin function for transfer function of output layer. Also Levenberg-Marquardt back propagation learning algorithm is used for training. Usually one hidden layer is enough but number of neurons in hidden layer need to be optimized for each problem. In order to optimization the number of neurons in hidden layer, average relative deviation (ARD) of testing data *versus* neuron number in hidden layer is plotted (Fig.1). Average relative deviation has been calculated by means of eqn. 4. Results showed 5-6-2 is the best topology of the neural network (Fig. 2).

$$\text{ARD} = \frac{100}{N} \times \sum_{i=1}^{N} \left| \frac{y^{\exp} - y^{\text{cal}}}{y^{\exp}} \right| \quad (4)$$

After optimization of neural network, this model can be used as a high accurate relation. Results showed this model has an average relative deviation about 2.95 % and 3.4 %, respectively for training and testing subset. Although the accuracy of our proposed neural network is very high but the most advantage of this method is the ability of it for estimation of current density and voltage of fuel cell simultaneously.

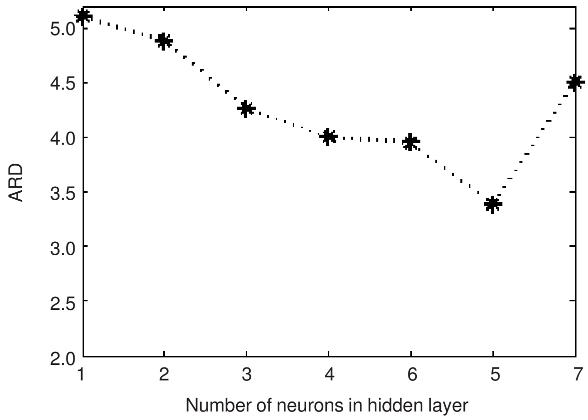


Fig. 1. ARD of testing data versus neuron number in hidden layer

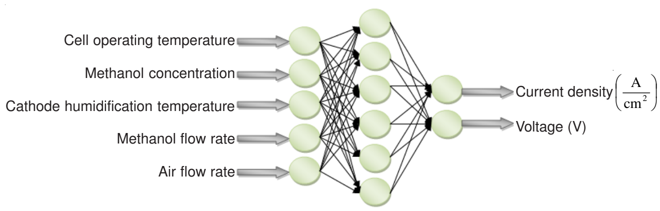


Fig. 2. Topology of our proposed neural network

Conclusion

In this work an artificial neural network with six neurons in hidden layer has been used for performance prediction of direct methanol fuel cell. Our proposed model has an average relative deviation about 2.95 % and 3.4 % respectively for training and testing subset. The most advantage of this method is the ability of it for estimation of current density and voltage of fuel cell simultaneously.

ACKNOWLEDGEMENTS

This work was sponsored by the Renewable Energy Organization of Iran. The authors wish to thank the Renewable Energy Organization of Iran.

REFERENCES

1. J.-H. Lin, W.-H. Chen, Y.-J. Su and T.-H. Ko, *Fuel*, **87**, 2420 (2008).
2. T.S. Zhao, C. Xu, R. Chen and W.W. Yang, *Prog. Energ. Combust. Sci.*, **35**, 275 (2009).
3. T. Hatanaka, N. Hasegawa, A. Kamiya, M. Kawasumi, Y. Morimoto and K. Kawahara, *Fuel*, **81**, 2173 (2002).
4. D. Cheddie and N. Munroe, *J. Power Sourc.*, **147**, 72 (2005).
5. V.B. Oliveira, D.S. Falcão, C.M. Rangel and A.M.F.R. Pinto, *Int. J. Hyd. Energy*, **32**, 415 (2007).
6. R. Wang, L. Qi, X. Xie, Q. Ding, C. Li and C.M. Ma, *J. Power Sourc.*, **185**, 1201 (2008).
7. S. Ou and L.E.K. Achenie, *J. Power Sourc.*, **140**, 319 (2005).
8. A.U. Chávez-Ramírez, R. Muñoz-Guerrero, S.M. Durón-Torres, M. Ferraro, G. Brunaccini, F. Sergi, V. Antonucci and L.G. Arriaga, *Int. J. Hyd. Energy*, **35**, 12125 (2010).
9. Y. Vural, D.B. Ingham and M. Pourkashanian, *Int. J. Hyd. Energy*, **34**, 9181 (2009).
10. J. Ge and H. Liu, *J. Power Sourc.*, **142**, 56 (2005).