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NEURAL NETWORK APPROACH FOR PERFORMANCE PREDICTION OF A SOLID OXIDE FUEL CELL

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Abstract

In this study, we develop a neural network (NN) based model for performance prediction of a single tubular solid oxide fuel cell (SOFC). This model utilizes the back-propagation (BP) algorithm to predict the cell voltage and electrical power. Levenberg-Marquardt back-propagation algorithm based neural network has been used to develop the prediction model. The required data for learning process of the neural network model have been obtained from simulation results of a validated nonlinear physical SOFC model under wide operation range of the input variables. After neural network model development, comparisons of the simulation results of neural network model and the nonlinear physical model at the trained and untrained conditions have been carried out. As a result, it has been seen that the neural network model developed in this study is able to make good predictions in performance behavior of the considered fuel cell due to the training strategy and the topology of the neural network adopted.

Keywords: Solid oxide fuel cell; Performance prediction; Neural network model

1. Introduction

In recent years, solid oxide fuel cell (SOFC) has been considered as a highly promising candidate technology for near future distributed power applications from the viewpoints of energy and environment [1,2]. Solid oxide fuel cell has some unique advantages such fuel flexibility, high-energy conversion efficiency, low emissions, and useful waste heat for cogeneration and trigeneration applications [3-5]. The performance of the system depends on many factors, such as physical, chemical, electrochemical and thermodynamic processes.

Modeling studies of solid oxide fuel cell plays a significant role in the evaluation and prognostication of system performance, and in search of improvements in design, operating procedures and control strategies. Especially, modeling solid oxide fuel cell committed to distributed applications is crucial stage in the integration of these power sources into energy market. The application of solid oxide fuel cell in power generation entails a full knowledge of its behavior and therefore a highly efficient model. Hence, detailed and complex modelling is required for predicting the performance of the fuel cell and for use in various systems engineering activities considering all the above factors.

Although physical models present comprehensive analysis of the performance, they are very time-consuming to develop and run. The computations become quite complex, especially when models dimensions are two-three level. Therefore, there has been recent interest in building neural network (NN) models. Neural Network have been used in a wide range of engineering applications such as, pattern recognition, behavior prediction and function approximations [6-8].

In this study, we develop a neural network based model for performance prediction of a single tubular solid oxide fuel cell. This model utilizes the back-propagation (BP) algorithm to predict the cell voltage and electrical power of the solid oxide fuel cell. After neural network model development, the prediction of the neural network model are given and evaluated with those of physical nonlinear model. As a result, it has been

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concluded that the Levenberg-Marquardt back-propagation algorithm based neural network structure have been very appropriate to model the nonlinear dependence of SOFC performance.

2. Development of Neural Network Model

2.1 Neural Network Structure

Neural networks are considered to be sophisticated modeling techniques capable of modeling extremely complex nonlinear functions, which consists of links connected nodes. Their structure is analogous to that of neural system in human brain by which nodes correspond to neurons and links correspond to synapses that transmit signals between neurons. One of the major features of a neural network is its learning capability [9]. Artificial neural networks try to mimic this biological network in order to learn the solution to a physical problem from a given set of training sets.

Important issues in neural network structure include specification of the number of hidden layers and the number of units in these layers. The number of input and output units is defined by the problem. This point requires some knowledge about the behavior of the system to model and especially about the factors that condition the system output. The most significant parameters have been maintained in order to obtain an excellent model requiring as low number of measurements as possible.

Figure 1 shows the neural network structure considered in this study. A three-layer neural network with tan-sigmoid transfer function at first hidden layer, linear transfer function at second hidden layer and a linear transfer function at output layer has been used. This neural network structure has three inputs and two output variables.

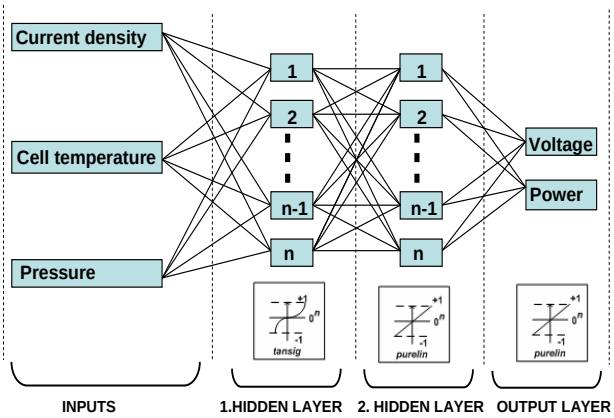

Figure 1. Neural network structure for SOFC performance prediction

The data used in this paper have been gathered from the simulation of tubular solid oxide fuel cell physical model for the wide range of its operation The detailed information for the solid oxide fuel cell physical model can be found author's previous studies [10,11]. Using the mentioned physical model, the performance values such as voltage and electrical power have been gathered for wide operation range of the input variables, and the values have been used to train the neural network prediction model.

2.2 Input and Output Parameters

Table 1 shows the input and output variables of the solid oxide fuel cell used for the development of the neural network performance prediction model. The three input variables have been selected for modeling of the performance of solid oxide fuel cell. They are cell temperature, operating pressure and current density. The characteristics of these input parameters help to explain mainly the solid oxide fuel cell performance. These variable ranges have been given in Table 1. The outputs of neural network model considered are the cell voltage and electrical power, which are the indicators of solid oxide fuel cell performance.

The performance data (cell voltage and electrical power) have been obtained from physical model simulation through the variation of current density in its possible entire range at the certain cell temperature and operating pressure. The base case values of cell temperature and operating pressure have been considered as

1273 ^{o}C and 1.08 bar, respectively. A number of performance data have been gathered at the different temperature and pressure. By means of this way, 700 sample data have been obtained for neural network training.

Table 1. Input and output variables for the NN-PM model

Variables	Value
Input variables	
Current density (A/m^2)	1-8830
Cell temperature (^{o}C)	1073, 1173, 1273, 1373
Operating pressure (bar)	1.08, 3, 5, 10
Output variables	
Voltage (V)	0-0.95
Power (kW)	0-429.1

2.3 Training Neural Network

In the training stage, input and output values of the 700 sample data for training have been supplied. Using these values, the network tries to learn the system by adjusting the weights. This is adapted by the back propagation algorithms. Gathered data obtained from physical model have been used to train the network. Once the network is trained, it moves to the testing stage. In the testing stage also, both input and output values were supplied. The only difference between the testing and training stage is that there is no adjustment of weights in the testing stage. Adjustment of weights, in other words learning, takes place only in the training stage. Neuron numbers at the hidden layers for Levenberg-Marquardt algorithm has been decided by trial-error studies. They have been determined as 8 and 25 neurons for first and second hidden layers, respectively in this study.

3. Modeling Results and Discussion

Figure 2 shows training mean square error for Levenberg-Marquardt algorithm. The training stopped after 73 iterations because the mean square error on a performance estimation set reaches a minimum value (0.000827).

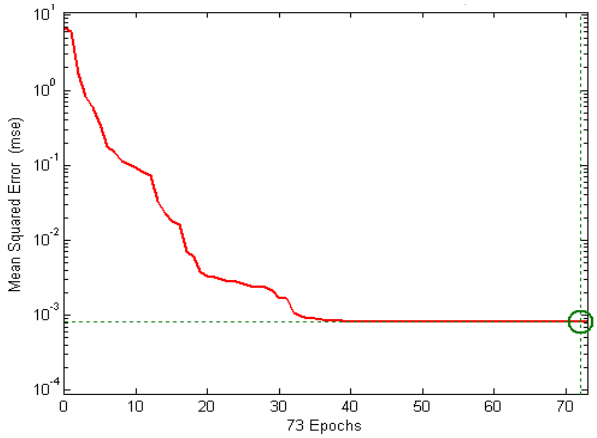

Figure 2. Training mean squared errors for Levenberg-Marquardt algorithm

Figure 3 illustrates the prediction results for cell voltage and electrical power versus current density at the P=1.08 bar, T=1273 ^{o}C (trained conditions). There is very good agreements on the trends between gathered data from solid oxide fuel cell physical model and estimated from neural network model for both cell voltage and electrical power except the end of current density values. The voltage and power errors at the current density of approximately 6000 A/m^2 increase rapidly.

This situation can be explained that although there is rapid variation in the performance values, a limited training data samples are used in comparison to the lower current density conditions. If it could be possible to give more data at these conditions, the error values of neural network model would be smaller.

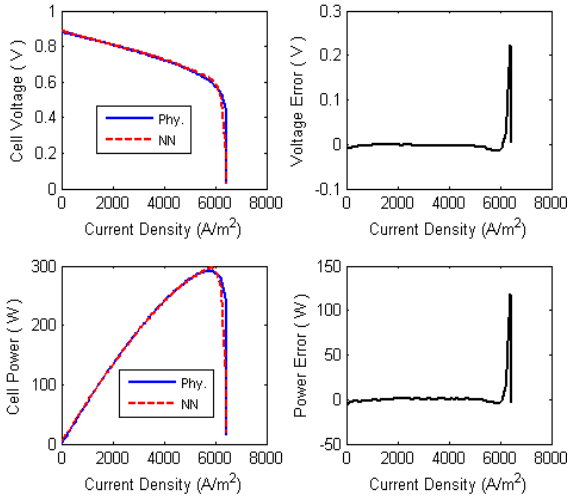

Figure 3. Comparison of predicted and gathered data for cell voltage and power (P=1.08 bar, T=1273 ^{o}C)

Figure 4 shows the prediction results of the developed neural network model for cell voltage and electrical power versus current density at untrained cell temperature condition (P=1.08 bar, T=1223 ^{o}C). The errors of both voltage and power show similar characteristics with those of trained temperature condition (Figure 3).

It can be noted that although this temperature condition (1123 ^{o}C) is untrained, the errors are smaller at the higher current density conditions (approximately 6000 A/m^2). These behaviors prove the prediction capability of the developed neural network model.

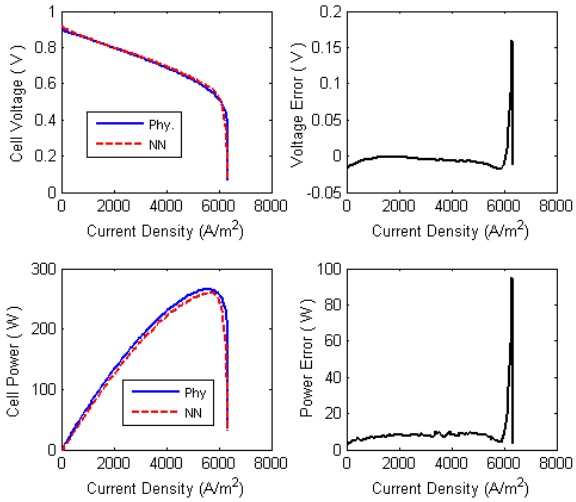

Figure 4. Comparison of predicted and gathered data for cell voltage and power (P=1.08 bar, T=1223 ^{o}C)

Figure 5 and Figure 6 depict the prediction performance of the developed neural network model for trained pressure (P=10 bar, T=1273 ^{o}C) and untrained pressure conditions (P=8 bar, T=1273 ^{o}C). Since the neural network model is trained at the pressure of 10 bar condition, the prediction performance is very well. The prediction errors are relatively higher at the pressure of 8 bar condition However, it is clearly seen from these figures that the developed NN model can enable to capture the general characteristics of the fuel cell performance, even untrained conditions.

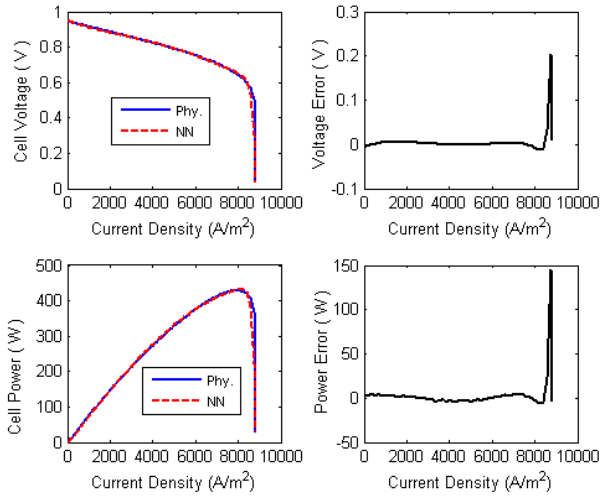

Figure 5. Comparison of predicted and gathered data for cell voltage and power (P=10 bar, T=1273 ^{o}C)

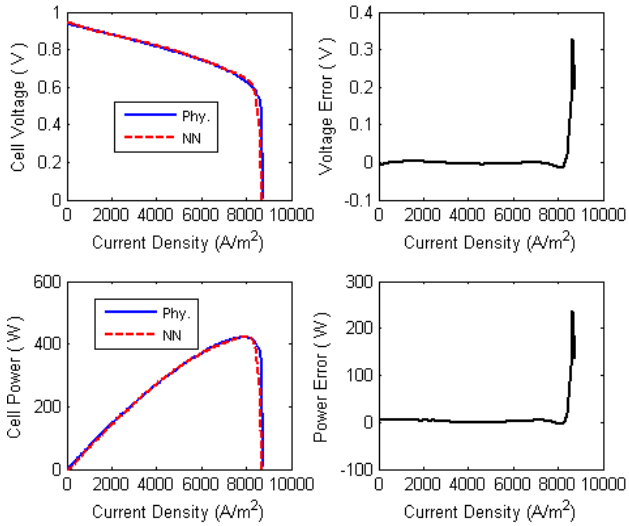

Figure 6. Comparison of predicted and gathered data for cell voltage and power (P=8 bar, T=1273 ^{o}C)

4. Conclusion

This study presents neural network model for performance prediction of a solid oxide fuel cell by considering the operating conditions as input parameters such as current density, operating pressure and cell temperature. The results of neural network model have been compared with the gathered data obtained from simulation results of the physical model of solid oxide fuel cell. It is seen that Levenberg-Marquardt back-propagation algorithm is a robust learning technique that capture the characteristics of the fuel cell performance. This paper indicates that the values predicted with the neural network can be used to predict the performance of the solid oxide fuel cell quite accurately for given conditions.

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