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# The optimal design for PEMFC modeling based on Taguchi method and genetic algorithm neural networks

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ABSTRACT

This paper has presented a new approach to estimate the output voltage of proton exchange membrane fuel cell (PEMFC) accurately by combining the use of a genetic algorithm neural networks (GANN) model and the Taguchi method. Using the PEMFC experimental data measured from performance test equipment of PEMFC, the GANN model could be trained and constructed for obtaining the steady state output voltage of PEMFC. Furthermore, in order to determine the important parameters in GANN, the Taguchi method is used for parameter optimization, with the goal of reducing the estimation error. The test equipment of PEMFC is accurate enough for acquiring the output voltage of PEMFC, and is quite useful for teaching purpose. However, taking the high cost, complicated operation procedure and environment safety into consideration, it is necessary to develop a simulation model of PEMFC to benefit teaching and R&D. Therefore, this paper will present an approach for constructing a GANN model with precise accuracy for the output voltage of PEMFC. For achieving the GANN model with high precision, a troublesome work has to be taken care of, that is, to determine all the parameters required in GANN. We will introduce Taguchi method to solve this problem as well. Finally, to show the superiority of proposed model, this approach has compared the estimation values of output voltage for PEMFC from GANN and BPNN models without using Taguchi method. One can easily find that the error of the proposed method is much smaller than that of the GANN model without Taguchi method and of the BPNN model; that is, the proposed approach has better performance on estimation for PEMFC output voltages.


## 1. Introduction

Fuel cell (FC) is an electrochemical device of power generation system that converts directly the chemical energy of fuels into electricity. Since fuel cells can offer a highly efficient environment and friendly electrochemical transformation for energy conversion; they are widely considered as a potential alternative power source and have drawn much attention and intensive development for commercial stationary power generation, residential applications, and transportation technologies in these days. A proton exchange membrane fuel cell operates typically at low temperature and can achieve many benefits, such as high power density, easy and safe operation mode, and compactness. With low-temperature operation and high power density, PEMFC is currently considered for power supply and propulsion of vehicle applications. In order to improve power quality, system performance and design optimization, the PEMFC system should be modeled and analyzed to give more insight for constructing the subsystems and interactions between them.

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**Nomenclature**

| | |
|---|---|
| $V_{FC}$ | output voltage of a single cell |
| $E_{Nernst}$ | thermodynamic potential of cell |
| $V_{act}$ | activation overpotential |
| $V_{ohmic}$ | Ohmic overpotential |
| $V_{con}$ | concentration overpotential |
| $T$ | cell temperature |
| $P_{H_2}$ | pressure of the hydrogen in the catalytic interface of the anode |
| $P_{O_2}$ | pressure of the oxygen in the catalytic interface of the cathode |
| $\xi_i$s | parametric coefficients |
| $C_{O_2}$ | concentration of oxygen in the catalytic interface of the cathode |
| $I$ | cell operating current |
| $C_{H_2}$ | concentration of hydrogen in the catalytic interface of the anode |
| $B$ | a constant depending on the cell and its operation state |
| $A_{rea}$ | cell active area |
| $J$ | actual current density of the cell |
| $J_{\max}$ | maximum current density of the cell |
| $R_M$ | equivalent membrane resistance due to proton conduction |
| $R_C$ | equivalent contact resistance due to electron conduction |
| $L$ | thickness of the membrane |
| $\rho_M$ | membrane specific resistivity |
| $n$ | number of cells |
| $x_1, x_2, \ldots x_i, \ldots, x_k$ | input variables of neural network |
| $w_{ji}$ | the ith weight of the jth neuron |
| $y_j$ | neuron output |
| $F(\bullet)$ | transfer function |
| $b_j$ | neuron bias |
| $k$ | number of input variables |
| $z$ | function variable |
| $O_i$ | real value |
| $E_i$ | estimated value |
| $m$ | number of samples |
| $\eta$ | learning rate |
| $\alpha$ | momentum factor |
| $\ell$ | number of iterations |
| $SSE$ | sum of square error |
| $g(\ell)$ | gradient of $SSE$ |
| $\nabla$ | gradient operator |
| $\tilde{y}_j$ | target value of the jth output |
| $m_p$ | total number of training output |
| $P_S$ | population size |
| $G_N$ | generation number |
| $C_R$ | crossover rate |
| $M_R$ | mutation rate |
| $(Z)_\phi$ | factor Z with Level $\phi$ |
| $V_r$ | output voltage of PEMFC measured from performance test equipment |
| $V_{SG}$ | estimated output voltage of PEMFC from GANN model with Taguchi method |
| $V_G$ | estimated output voltage of PEMFC from GANN model |
| $V_B$ | estimated output voltage of PEMFC from BPNN model |
| $\Delta E_1$ | absolute error of $V_r - V_{SG}$ |
| $(\Delta E_1)_{\max}$ | maximal value of $\{\Delta E_1\}$ |
| $\Delta E_2$ | absolute error of $V_r - V_G$ |
| $(\Delta E_2)_{\max}$ | maximal value of $\{\Delta E_2\}$ |
| $\Delta E_3$ | absolute error of $V_r - V_B$ |
| $(\Delta E_3)_{\max}$ | maximal value of $\{\Delta E_3\}$ |

There have been many studies on modeling and simulation of the PEMFC [1–6]. In [1], the authors developed a generalized steady-state electrochemical model for PEMFC to predict its performance. Dynamic modeling in the form of electrochemical circuits was developed in terms of an equivalent electrical circuit [2,3]. The nonlinear dynamic modeling of PEMFC system with reactant supply system was developed in [4] for the desired control objective. In particular, for the energy injected into the power grid with load variation, a model-based PEMFC is suitable for control system design to achieve high-efficiency performance and robust properties. Previous research [5,6] also discussed the dynamical behavior of unit cells and/or stacks, and presented some aspects related to the modeling parameters. These parameter values used are primarily derived from manufacturing data and laboratory experiments.

Recently, numerical modeling and computer simulation have been developed for better understanding of the fuel cell itself. A well-designed artificial neural network (ANN) model provides useful and reasonably accurate input–output relations because of its excellent multi-dimensional mapping capability. Artificial neural networks are computational paradigms made of massively interconnected adaptive processing units, known as neurons. They have been extensively employed in various areas of science and technology, such as pattern recognition, signal processing and process control in engineering [7]. However, the neural network applied to PEMFC systems for modeling and analyzing has receiving relatively little attention [7–12]. In [8], the neural network with back propagation method is adopted for modeling a PEMFC system. And its experimental data of PEMFC system can be fitted with the ANN model over a wide operating range. Based on neural network model, the authors in [9] have designed an adaptive controller to control the voltage in presence of fluctuations for PEMFC systems. In [10], the authors develop a static and dynamic model of a fuel cell by using ANN. In [11], due to the training strategy and the topology of the NN adopted, the authors propose an efficient static model for PEMFC with good predictions including durability consideration. In [7], using an ANN, the authors develop a non-parametric empirical model that could simulate the performance of PEMFC without extensive calculations. In [12], for avoiding the influence of uncertainty, the authors have proposed an adaptive PI control strategy using neural networks and adaptive Morlet wavelet to control the PEMFC system.

Taguchi method has been widely used in industry for the purpose of finding factors that are most important in achieving useful goals [13–17]. The main advantage of using the Taguchi method for optimization is that it uses orthogonal arrays to greatly simplify the task of planning experiments. In this paper, a model construction approach for PEMFC is proposed. We will carry out the experiments of PEMFC and collect the training data from performance test equipment, and these data will be used for neural network model construction to make sure the ability of precision and generalization. Here I should point out that some parameters for network structures and training process have to be determined. The different parameter combinations could be enormous and complicated, and thus these parameters are usually set by trial and error or by expert's knowledge. In [18,19] the investigations of using Taguchi method for parameter optimization in neural network were proposed. In this paper, four influential parameters, including population size, generations, crossover rate, and mutation rate, will be tuned off-line for constructing GANN.

The diagram of the proposed approach is shown in Fig. 1. Total 200 input-output pairs of five input variables and one output variable will be measured from performance test equipment of PEMFC to be the training data of GANN. The five input and one output variables are operation temperature, oxygen flow rate, hydrogen flow rate, load current, oxygen and hydrogen pressure, and output voltage. The training data will be used to construct the GANN. Four influential parameters, including population size, generations, crossover rate, and mutation rate, will be tuned off-line by Taguchi method. In each epoch, the error between the measured and estimated output voltage will be calculated, and the network is thus tuned and learned. There will be extra testing data collected from performance test equipment of PEMFC for verifying the generalization of GANN modeling performance. The superior performance will be shown in the experimental result and compared with other modeling method as well. Based on the proposed method for precise voltage estimation of PEMFC output voltages, we can better control and understand the PEMFC performance and operating status. Thus, it can be applied to the fields of electric bikes, electric motorcycles, and electric cars, etc. Also, it can be used as a simulation and test panel to benefit teaching and R&D.

The remainder of this paper is organized as follows. The principle of electricity generation for PEMFC and the performance test equipment of PEMFC are introduced in Section 2. Section 3 demonstrates the neural network modeling for PEMFC. The Taguchi method is discussed in Section 4, and experimental results are discussed in Section 5. Finally, conclusions are drawn in Section 6.

## 2. The principle of electricity generation for PEMFC and the performance test equipment

### 2.1. *Principle of electricity generation for PEMFC*

A typical structure of a single PEMFC is shown in Fig. 2. A single cell consists of an anode for the fuel and a cathode for the oxidant with an electrolyte that conducts ions between the two electrodes. At the anode, hydrogen molecules dissociate, the atoms are protonised, and electrons are directed to an external circuit to form electricity; protons migrate to the proton exchange membrane and pass through to the cathode, where oxygen combines with protons from the membrane and electrons from the external circuit to form water. The electrons passing from anode to cathode produce electrical energy.

According to the works of [1,5,20], the output voltage of a single cell can be defined by the following expression

$$V_{FC} = E_{Nernst} - V_{act} - V_{con} - V_{ohmic} \tag{1}$$

In the Eq. (1), $E_{Nernst}$ is the thermodynamic potential of the cell and represents its reversible voltage; $V_{act}$ is the voltage drop, associated with the electrodes, due to the activation of the anode and the cathode (activation overpotential); $V_{ohmic}$ is the Ohmic voltage drop (Ohmic overpotential), associated with the conduction of the protons in the solid electrolyte and internal electronic resistances; and $V_{con}$ represents the voltage drop resulting from the concentration or transport of mass of oxygen and hydrogen (concentration overpotential).

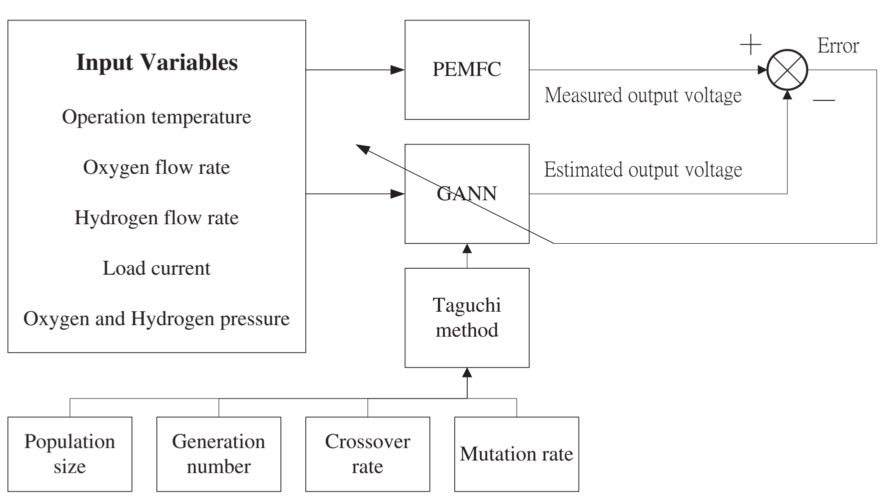


**Fig. 1 – Block diagram of the proposed approach.**

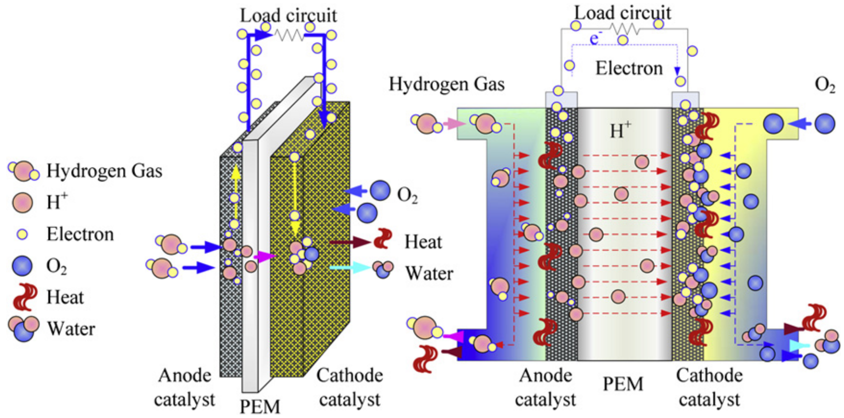


**Fig. 2 – Schematic of a PEMFC.**

The first term of (1) represents the PEMFC operation open-circuit-voltage (without load), while the three last terms represent reductions in this output voltage for the cell, $V_{FC}$, for a certain operation current. Each individual term of (1) is defined by [1,5,20]

$$E_{Nernst} = 1.229 - 0.85 \times 10^{-3}(T - 298.15) + 4.3085 \times 10^{-5} T(\ln P_{H_2} + 0.5 \times \ln P_{O_2}) \tag{2}$$

$$V_{act} = -(\xi_1 + \xi_2 \times T + \xi_3 \times T \times \ln(C_{O_2}) + \xi_4 \times T \times \ln(I)) \tag{3}$$

$$C_{O_2} = \frac{P_{O_2}}{5.08 \times 10^6 \exp\left(\frac{-498}{T}\right)} \tag{4}$$

$$\xi_2 = 0.00286 + 0.0002 \times \ln A_{rea} + 4.3 \times 10^{-5} \times \ln C_{H_2} \tag{5}$$

$$C_{H_2} = \frac{P_{H_2}}{1.09 \times 10^6 \exp\left(\frac{77}{T}\right)} \tag{6}$$

$$V_{con} = -B \times \ln\left(1 - \frac{J}{J_{max}}\right) \tag{7}$$

$$V_{ohmic} = I \times (R_M + R_C) \tag{8}$$

where $T$ is the cell temperature ($K$), $P_{H_2}$ and $P_{O_2}$ are the pressure (atm) of hydrogen and oxygen, respectively, $I$ is the cell operating current (A), $\xi_i$s represent parametric coefficients for cell model, $C_{O_2}$ is the concentration of oxygen in the catalytic interface of the cathode (mol/cm$^3$), $C_{H_2}$ is the concentration of hydrogen in the catalytic interface of the anode (mol/cm$^3$), and $A_{rea}$ is the cell active area (cm$^2$). The $B$ (V) is a constant depending on the cell and its operation state, $J$ and $J_{max}$ represent the actual current density and maximum current density of the cell (mA/cm$^2$), respectively. $R_M$ is the equivalent membrane resistance due to proton conduction, and $R_C$ is the equivalent contact resistance due to electron conduction.

Furthermore, the equivalent resistance of the membrane $R_M$ can be calculated by

$$R_M = \frac{\rho_M \times L}{A_{rea}} \tag{9}$$

in which $L$ is the thickness of the membrane (cm). $\rho_M$ is the membrane specific resistivity (Ω cm) obtained by

$$\rho_M = \frac{181.6\left[1 + 0.03\left(\frac{I}{A_{rea}}\right) + 0.062\left(\frac{T}{303}\right)^2\left(\frac{I}{A_{rea}}\right)^{2.5}\right]}{\left[\lambda - 0.634 - 3\left(\frac{I}{A_{rea}}\right)\right] \times \exp\left[4.18\left(\frac{T - 303.15}{T}\right)\right]} \tag{10}$$

where 181.6/(λ − 0.634) is the specific resistivity (Ω cm) at zero current ($I = 0$) and temperature of 30 °C ($T = 303.15$ K). The parametric coefficient $\lambda$ is considered as an adjustable parameter with a possible minimum value of 14 and a maximum value of 23 (see Remark 1).

**Remark 1:** Referring to reference [6], one knows that the parameter λ will be influenced by the membrane preparation procedure and also affected by the relative humidity and stoichiometric ratio of the anode feed gas.

**Remark 2**: The Eq. (1) is the output voltage of a single cell. If the PEMFC stack which consists of $n$ cells (regarding as $n$ cells connected with series) is taken for consideration, then the output voltage of PEMFC stack can be expressed as $V_{FC}|_{stack} = n \times (E_{Nernst} - V_{act} - V_{con} - V_{ohmic})$.

From the above Eqns. (1)–(10), one can find that the values of coefficients ($\xi_i$s) in an empirical equation vary depending on the physical properties and process operating conditions. The correct mathematical relations between these coefficients and the physical properties or a control condition are not defined well. To avoid the calculation procedure for these coefficients over a wide of operating conditions, non-parametric techniques using an ANN to model the PEMFC single cell is developed in this paper. Consequently, we will construct an ANN with genetic algorithm for modeling a PEMFC. And, with the aid of Taguchi method, the better performance on estimation for PEMFC output voltages can be achieved.

### 2.2. *Description of performance test equipment of PEMFC*

The performance test equipment of PEMFC (see Fig. 3) is used to observe the output characteristics by measuring the output power, voltage, and current and by controlling and modifying load current, PEMFC temperature, fuel flow rate, fuel pressure, fuel humidity, and fuel temperature. From the experiments,

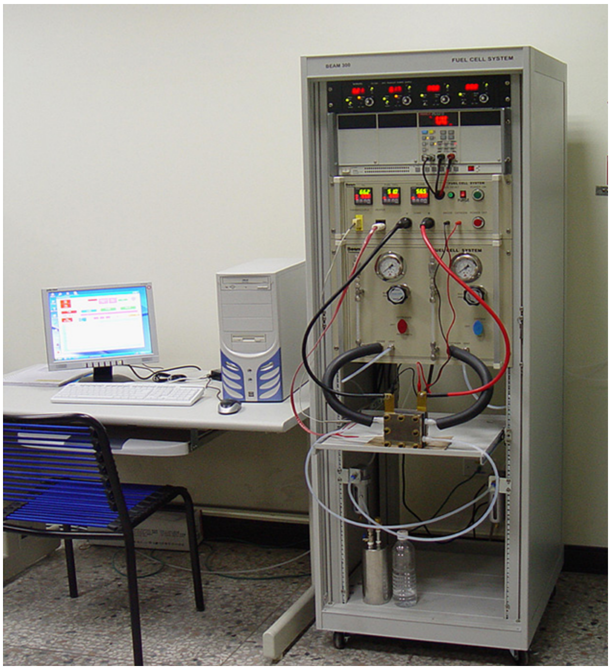

Fig. 3 – Performance test equipment of PEMFC.

we can get the conclusion that the fuel waste could be reduced if the fuel flow supply is just enough for the output requirement of PEMFC. On top of that, better performance can be achieved by fine tuning the operation parameters, such as load current, temperature of PEMFC, fuel pressure, fuel flow rate, and etc.

There are four modes in the PEMFC performance test equipment, including constant voltage (CV), constant current (CC), constant power (CP) and constant resistance (CR). In this paper, the constant current mode is adopted for the performance test equipment of PEMFC.

**Remark 3**: Here, I should point out that the five parameters of input data (shown in Fig. 1) are measured from PEMFC test equipment. And these five parameters are controlled by PEMFC test equipment with program setting. The interested readers could refer to [20] for more information.

## 3. The neural network modeling for PEMFC

The neural network has been developed rapidly in recent decades. There have been many successful application examples in all kinds of fields, such as biology, medical science, agriculture, mechanical engineering, automatic control, and etc. The structure of its basic component is very simple. The weights could be modified by the transfer function and by using different methods to link the input, output, and hidden layers. Then the constructed neural network could receive, process, and output the data rapidly with good performance. Furthermore, the constructed NN model can be applied to the fields of system performance estimation, system performance simulation, system failure diagnosis, and system parameter optimization [21]. The main advantage of neural network is the excellent nonlinear approximation ability, and there will be fewer assumptions for model construction compared to the traditional statistic models. The mathematical model of PEMFC is with physics, electrochemistry and heat conduction meanings, however, its derivation process is very complicated and the effectiveness is not as good as the neural network model. Therefore, the neural network is very good for model construction of PEMFC.

### 3.1. *Neural network model*

Fig. 4 is the basic structure of neural networks [22,23]. The $k$ inputs ($x_1, x_2, \ldots x_i, \ldots, x_k$) and one bias input $b_j$ are linked to the $j$th neuron. The output of the $j$th neuron will be:

$$y_j = F\left(\sum_{i=1}^{k} w_{ji}x_i - b_j\right) \tag{11}$$

where $y_j$ is the neuron output, $F(\cdot)$ is the transfer function, $w_{ji}$ is the $i$th weights of the $j$th neuron, $x_i$ is the neuron input layer parameter, $b_j$ is the neuron bias, and $k$ is the number of inputs. Here, the transfer function is chosen as a sigmoid function shown in Eq. (12).

$$F(z) = \frac{1}{1+e^{-z}} \tag{12}$$

where $z$ is the function variable. To match with Eq. (11), $z$ can be expressed as $z = \sum_{i=1}^{k} w_{ji}x_i - b_j$.

In this paper, the architecture of the ANN could be divided into the input layer with 5 neurons (for 5 input variables), the output layer with 1 neuron (for 1 output variables), and the hidden layer with 11 neurons (see Remark 7). And a transfer function is used as a sigmoid function. Furthermore, to show the superiority of proposed model (Taguchi method and GANN), this approach will compare the estimation values of output voltage for PEMFC from GANN and BPNN models without using Taguchi method. Then, the learning algorithm of BPNN and GANN should be expressed with brief and detail, respectively. And they can be found in Remark 4 and subsection 3.2, respectively.

In order to verify the learning performance of the neural network, this paper uses root mean square error (RMSE) for performance evaluation of GANN. The RMSE is defined as follows:

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{m}(O_i - E_i)^2}{m}} \tag{13}$$

where $O_i$ is the real value, $E_i$ is the estimated value, and $m$ is the number of samples.

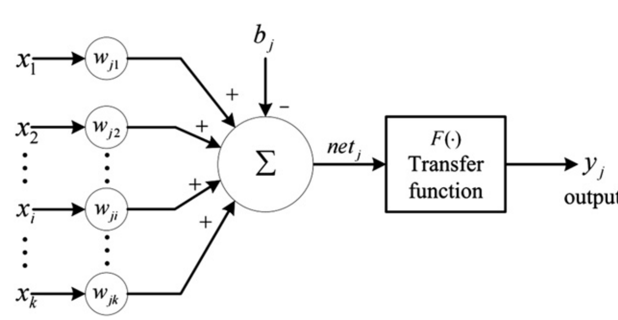


Fig. 4 – The structure of neural networks.

**Table 1 – Control factors and level settings for Taguchi experiments.**

| Control Factors | Levels | | |
|---|---|---|---|
| | Level 1 | Level 2 | Level 3 |
| $P_S$ | 40 | 60 | 80 |
| $G_N$ | 100 | 150 | 200 |
| $C_R$ | 0.7 | 0.8 | 0.9 |
| $M_R$ | 0.05 | 0.1 | 0.2 |

**Remark 4**: The learning algorithm of BPNN is that the ANN is trained by updating the weights using a back propagation learning rule. And the learning rule can be expressed as $w_{ji}(\ell+1) = w_{ji}(\ell) - \eta g(\ell) + \alpha(w_{ji}(\ell) - w_{ji}(\ell-1))$. Where $\eta$ is the learning rate, $\alpha$ is called the momentum factor, $w_{ji}(\ell-1)$ is the previous state of $w_{ji}(\ell)$, $w_{ji}(\ell+1)$ is the next state of $w_{ji}(\ell)$, $\ell$ is the number of iterations and $g(\ell)$is the gradient of sum of square error ($SSE$) when $w_{ji} = w_{ji}(\ell)$, *i. e.*

$$g(\ell) = \frac{\partial(SSE)}{\partial w_{ji}}\bigg|_{w_{ji}=w_{ji}(\ell)} = \nabla(SSE)\Big|_{w_{ji}=w_{ji}(\ell)}.$$

In which $SSE$ is defined as $SSE = \sum_{j=1}^{m_p}(\tilde{y}_j - y_j)^2$. Where $\tilde{y}_j$ is the target value for the $j$th output, $y_j$ is the actual value for the $j$th output, and $m_p$ is the total number of training output.

### 3.2. *Genetic algorithm*

Genetic algorithm [24] is based on the Darwinian law of survival of the fitness, that is, some parents with stronger fitness ability to the environment will be chosen. The genes of these parents will be exchanged with each other to produce the offspring. By this way, some offspring are expected to be with higher fitness than their parents, since the good genes would be preserved and the chromosome could become even better after the crossover operation. With the processes of crossover, reproduction, and selection, the best chromosome with the strongest fitness ability to the environment eventually will be evolved in the end.

Genetic algorithm uses three basic operation mechanisms to imitate the process of natural inheritance. They are called reproduction, crossover, and mutation. With the evolving processes of these three operations, the offspring will be produced by its parents. A fitness function, which represents the fitness ability to the environment for a chromosome, has to be defined first. Then all the chromosomes will be evaluated by the fitness function, and the selection operation will choose the chromosomes with better fitness values to be the offspring. The descriptions of fitness function and selection operation are as following:

(1) Fitness function

Fitness function could be considered as how the Mother Nature evaluates the fitness value of each chromosome to the environment. The genetic algorithm process will try to search for the chromosome with the best fitness value. In this paper, the best fitness value equals to the minimum error. The fitness function is defined as:

$$fitness = \frac{1}{1 + error} \tag{14}$$

In which the error is mostly adopted with the value of RMSE.

(2) Selection operation

A population will be composed of a group of chromosomes. Selection operation is to choose the chromosomes with better fitness values in this generation, and the chosen ones will be preserved to be the offspring. There are several methods of selection operation, and here we will introduce two common ones:

A. Roulette-wheel selection

In a population, each chromosome will have its own area on the Roulette-wheel, and the size of the area will be directly proportional to its own fitness value. Thus, the chromosome with higher fitness value will have a larger area. For each chromosome, the larger its area is, the better opportunity it will be chosen and preserved to the next generation. The advantage of the Roulette-wheel selection is that there is a chance that some weaker solutions may survive through the selection process, as though a solution may be weak, it may include some components which could prove useful following the recombination process. The drawback is that the local maximum could be easily obtained in the beginning of the search process.

**Table 2 – Experiment results and S/N ratios.**

| Experiments No. | Control factors | | | | Experiment results | |
|---|---|---|---|---|---|---|
| | $P_S$ | $G_N$ | $C_R$ | $M_R$ | RMSE (V) | S/N(dB) |
| (1) | Level 1 | Level 1 | Level 1 | Level 1 | 0.03985 | 27.991 |
| (2) | Level 1 | Level 2 | Level 2 | Level 2 | 0.05061 | 25.915 |
| (3) | Level 1 | Level 3 | Level 3 | Level 3 | 0.05112 | 25.828 |
| (4) | Level 2 | Level 1 | Level 2 | Level 3 | 0.05551 | 25.113 |
| (5) | Level 2 | Level 2 | Level 3 | Level 1 | 0.0437 | 27.19 |
| (6) | Level 2 | Level 3 | Level 1 | Level 2 | 0.09328 | 20.604 |
| (7) | Level 3 | Level 1 | Level 3 | Level 2 | 0.06231 | 24.109 |
| (8) | Level 3 | Level 2 | Level 1 | Level 3 | 0.07475 | 22.528 |
| (9) | Level 3 | Level 3 | Level 2 | Level 1 | 0.04648 | 26.655 |

**Table 3 – Level analysis of S/N ratios.**

| S/N(dB) | Control factors | | | |
|---|---|---|---|---|
| | $P_S$ | $G_N$ | $C_R$ | $M_R$ |
| Level 1 | 26.578 | 25.738 | 23.708 | 27.279 |
| Level 2 | 24.302 | 25.211 | 25.894 | 23.543 |
| Level 3 | 24.43 | 24.362 | 25.709 | 24.49 |

B. Tournament selection

In tournament selection, two chromosomes are randomly selected, and their fitness values will be compared to each other. The one with better fitness value will be the offspring. The advantage of tournament selection comparing to the Roulette-wheel selection is that the local maximum will not be obtained in the early stage, thus, the problem of early convergence could be avoided.

**Remark 5:** The Tournament selection is used in this paper.

## 4. Taguchi method

Taguchi method, also called Taguchi quality engineering, is founded in 1949. The founder is Dr. Genich Taguchi, and he developed this method in Nippon Telephones and Telegraph Company when he was doing the research of a communication system [25,26]. In this paper, Taguchi method is used to characterize the various control factors for GANN model and to estimate the output voltage of PEMFC precisely. The most important tools of Taguchi method are orthogonal arrays and Signal-to-Noise (S/N) ratios [27]. We will introduce the meaning and usage of orthogonal arrays and S/N ratios in the following subsections.

### 4.1. *Orthogonal array*

The purpose of orthogonal arrays is that with minimum simulations, the required result could be obtained by analyzing and matching these simulations. An orthogonal array is a fractional factorial matrix, which assures a balanced comparison of levels of any factor or interaction of factors. It is a matrix of numbers arranged in rows and columns where each row represents the level of the factors in each run, and each column represents a specific factor (control factor) that can be changed from each run. The array is called orthogonal because all columns can be evaluated independently. The typical orthogonal array is in the form of $L_a(b^c)$, which means that there are $a$ experiments and $c$ factors which could at most contain $b$ levels. It also represents an orthogonal array with $a$ rows and $c$ columns. Letter $L$ stands for the first letter of Latin Squares, which is the original name of orthogonal array [28]. In this paper, three-level orthogonal arrays are used. The three-level orthogonal arrays that most often used in practice are $L_9(3^4)$, $L_{18}(2^1 \times 3^7)$, $L_{27}(3^{13})$, $L_{36}(2^{11} \times 3^{12})$, $L_{36}(2^3 \times 3^{13})$ and $L_{54}(2^1 \times 3^{25})$. The orthogonal array $L_9(3^4)$ is used in this paper. Additional details and the detailed description of other-level orthogonal arrays can be found in the books by Montgomery [29], Phadke [30], and Park [31].

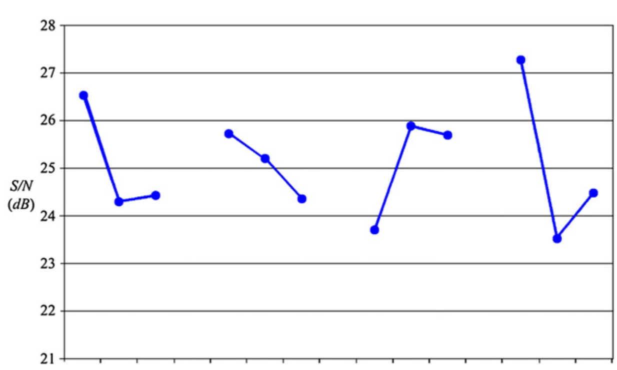


**Fig. 5 – Level analysis and factor effects of S/N ratios.**

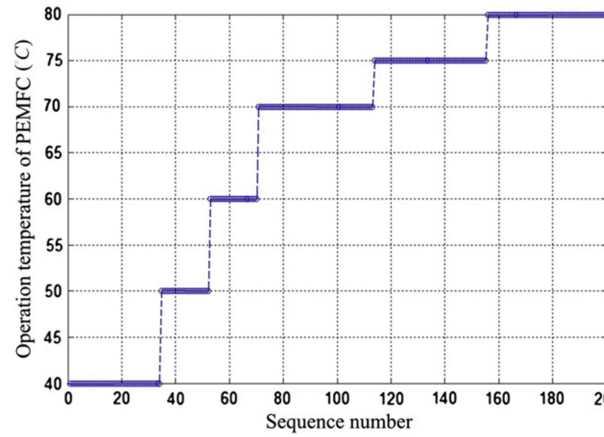


**Fig. 6 – PEMFC operation temperature.**

### 4.2. *S/N ratios*

Dr. Taguchi has participated in many quality improvement projects. In communication engineering, S/N ratios are frequently used as the quality index. Thus, no matter the to-be-solved problem is related to signals and noises or not, the quality index will always be used as Signal-and-Noise ratios, or S/N ratios in short. There are several S/N ratios available depending on the interested type of characteristics: Nominal

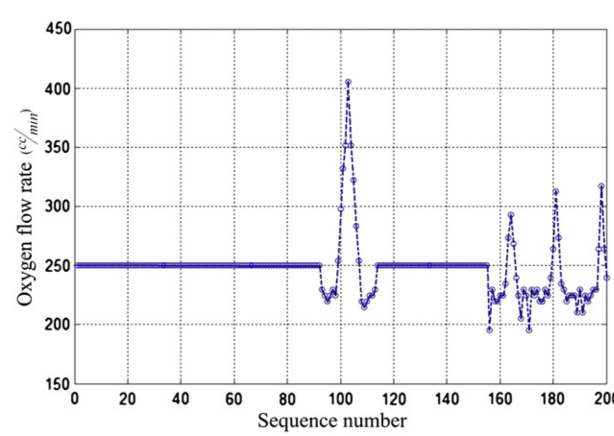


**Fig. 7 – Oxygen flow rate.**

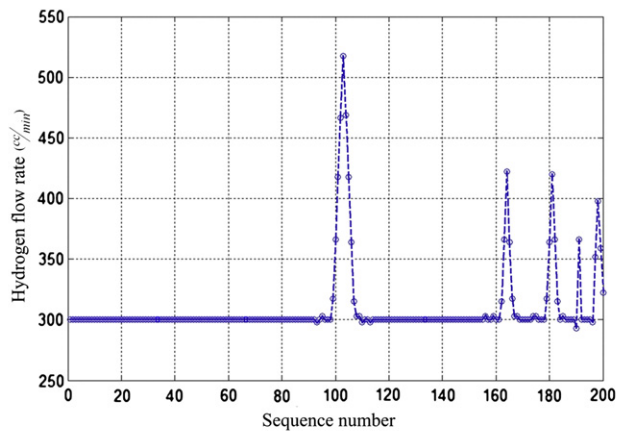


Fig. 8 – Hydrogen flow rate.

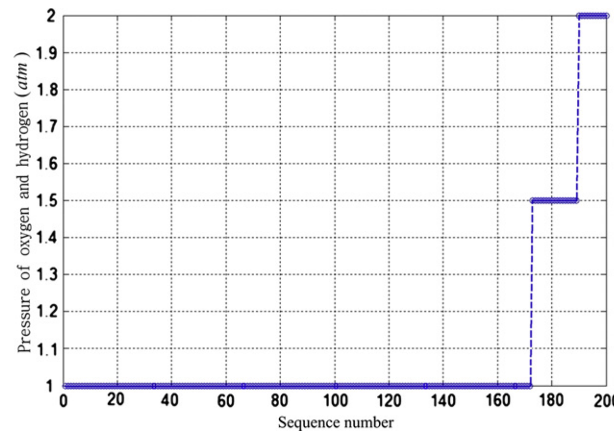


Fig. 10 – Pressure of oxygen and hydrogen.

the Best, Smaller the Better, and Larger the Better. In this paper, Smaller the Better is used to evaluate the RMSE of GANN. The Smaller the Better considers the smallest value as the best quality [16]. The formula of S/N ratio is shown as below [32]:

$$S/N = -10\log\left(\frac{1}{m}\sum_{i=1}^{m}(O_i - E_i)^2\right) \tag{15}$$

where $O_i$ is the real value, $E_i$ is the estimated value, and $m$ is the number of samples.

## 5. Experiment steps

This paper focuses on the operation mode of steady state response of PEMFC. CC mode has been used for PEMFC performance test equipment, and the network parameters will be tuned off-line through Taguchi method. A set of real experiment data will be collected and taken as training data for determining the weights and biases of GANN. Finally, several real data from other experiment are collected as testing data and compared with the counterparts, that is, the model outputs of GANN, to verify the modeling performance. We will describe all the processes in detail in this section.

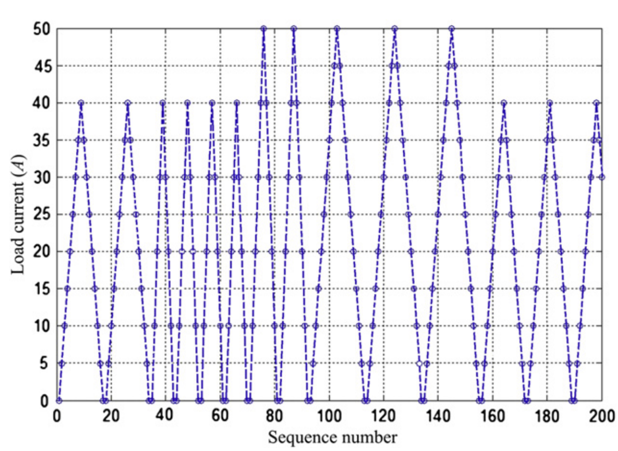


Fig. 9 – Load current.

### 5.1. *GANN parameter optimization by Taguchi method*

Taguchi method will be used in off-line mode to optimize four most important and influential parameters of GANN, which are defined as the control factors, such as the population size ($P_S$), the generation number ($G_N$), the crossover rate ($C_R$), and the mutation rate ($M_R$). The control factors and levels are set in Table 1 (please refer to Remark 6):

In this paper, 200 real experimental data samples are utilized as training data. Each quality level of the four factors is then assigned to the $L_9(3^4)$ orthogonal array. The RMSE of GANN will be used as the Smaller the Better index. In each experiment, the RMSE and S/N ratios will be calculated by (13) and (15), respectively, and shown in Table 2. Finally, S/N ratios will be used for level analysis, which are shown in Table 3 and Fig. 5.

In Fig. 5, the $(Z)_\phi = P_s, G_N, C_R, M_R$ and $\phi = 1, 2, 3$, denotes the factor Z with Level $\phi$. Here, our target is to make RMSE to be as small as possible. Thus, from the level analysis of Table 3 and Fig. 5, the optimized parameter for the four control factors should be $(P_S)_1$, $(G_N)_1$, $(C_R)_2$, and $(M_R)_1$. By matching with Table 1, these four parameters could be determined as: the population size: 40, the generation number: 100, the crossover rate: 0.8, and the mutation rate: 0.05.

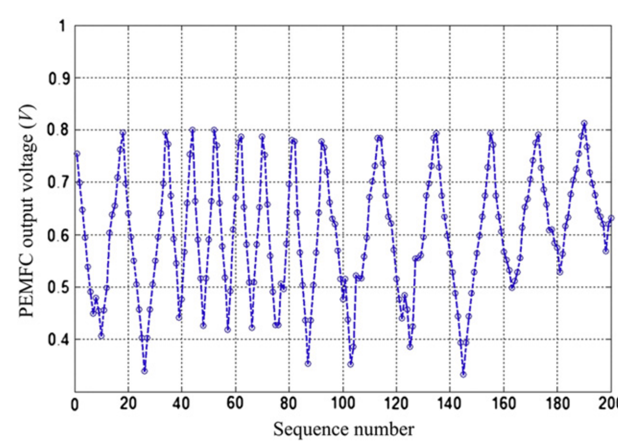


Fig. 11 – The output voltage of PEMFC measured from performance test equipment.

**Table 4 – Parameter settings of GANN model with Taguchi method.**

| | | | |
|---|---|---|---|
| Input variables: | 5 | population size($P_S$) | 40 |
| Output variables: | 1 | generation number($G_R$) | 100 |
| Experimental data samples (for Training): | 200 | crossover rate($C_R$) | 0.8 |
| Value of random number seed: | 0.456 | mutation rate($M_R$) | 0.05 |

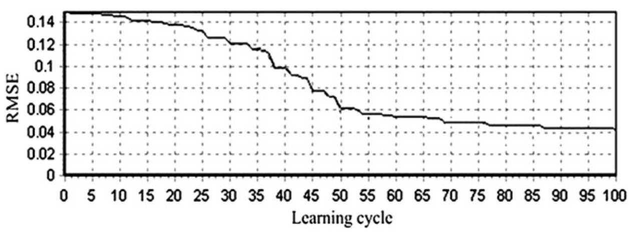


**Fig. 12 – RMSE convergence result of GANN model with Taguchi method.**

### 5.2. *PEMFC modeling and verification*

The aforementioned optimized parameters are for constructing the PEMFC model. The package software used in this paper is Super PCNeuron 5.0 standard version. The training data are collected from real experiments by performance test equipment of PEMFC. There are five input variables ($x_1$, $x_2$,…, $x_5$) and one output variable ($y_1$) in the training data. $x_1$ is the operation temperature of PEMFC (shown in Fig. 6), $x_2$ is the oxygen flow rate (shown in Fig. 7), $x_3$ is the hydrogen flow rate (shown in Fig. 8), $x_4$ is load current (shown in Fig. 9), $x_5$ is the pressure of oxygen and hydrogen (shown in Fig. 10), and $y_1$ is the PEMFC output voltage which is measured from real experiments (shown in Fig. 11). Once the training data containing the abovementioned five input variables and one output variable have been collected, they will be fed to the GANN, whose parameters are set in Table 4. The final RMSE convergence result of GANN will be plotted by the application software and is shown in Fig. 12. Here, I should point out that the number of neurons used in hidden layer is 11.

### 5.3. *Real measurements and model estimation*

The GANN has been completely constructed in subsection 5.2. In order to verify the accuracy and performance of the model, we do the experiment again and collect another six data to be the testing data. The experiment is under the conditions of below: the operation temperature is 80 (°C), the oxygen and hydrogen flow rates are sufficient, the pressure of oxygen or hydrogen is 2 (atm), and the load current is from 0 (A) to 25 (A), with each increment of 5 (A). The six testing data are shown in Table 5, and the output voltages ($V_r$) of these six experiments are recorded. In the estimation stage, the five input variables of the six testing data shown in Table 5 are the inputs of the constructed GANN model, and the result (estimated output voltage) is shown in Table 6.

**Table 6 – The GANN estimation result for the six testing data.**

| Six testing data | Output variable |
|---|---|
| | $V_{SG}$ (V) |
| 1st datum | 0.7826238 |
| 2nd datum | 0.7801108 |
| 3rd datum | 0.7732638 |
| 4th datum | 0.7671335 |
| 5th datum | 0.7171009 |
| 6th datum | 0.7111704 |

In order to check the accuracy of the constructed GANN model, we calculate the absolute error and the maximal error, which are shown in the follows:

$$\Delta E_1 = |V_r - V_{SG}| \tag{16}$$

$$(\Delta E_1)_{max} = \{\Delta E_1\} \tag{17}$$

where $V_r$ is the output voltage of PEMFC measured from performance test equipment, $V_{SG}$ is the estimated output voltage of PEMFC from GANN model with Taguchi method, $\Delta E_1$ is the absolute error of $V_r - V_{SG}$, and $(\Delta E_1)_{max}$ is the maximal value of $\{\Delta E_1\}$.

The absolute error and maximal error between the measured and estimated output voltages of the six testing data are calculated from (16) and (17) and shown in Table 7.

### 5.4. *Result verification and discussion*

In subsection 5.3 we have proposed the result between the measured testing data and the ones estimated by GANN model with Taguchi method. In order to show the modeling performance and accurate estimation on PEMFC for our proposed method, two models are chosen for comparisons in this subsection.

**Table 5 – The six testing data.**

| Six testing data | Five input variables | | | | | Output variable |
|---|---|---|---|---|---|---|
| | $x_1$ ( C) | $x_2$ (cc/min) | $x_3$ (cc/min) | $x_4$ (A) | $x_5$ (atm) | $V_r$ (V) |
| 1st datum | 80 | 219.7 | 41.5 | 0 | 2 | 0.838 |
| 2nd datum | 80 | 224.6 | 70.8 | 4.99 | 2 | 0.798 |
| 3rd datum | 80 | 214.8 | 41.5 | 10.01 | 2 | 0.77 |
| 4th datum | 80 | 229.5 | 68.4 | 14.99 | 2 | 0.73 |
| 5th datum | 80 | 219.7 | 295.4 | 19.99 | 2 | 0.702 |
| 6th datum | 80 | 219.7 | 271 | 24.98 | 2 | 0.662 |

**Table 7 – The absolute error and maximal error between the measured and estimated voltages by GANN (with Taguchi method).**

| $V_r$ (V) | $V_{SG}$ (V) | $\Delta E_1$ (V) |
|---|---|---|
| 0.838 | 0.7826238 | 0.0553762 |
| 0.798 | 0.7801108 | 0.0178892 |
| 0.77 | 0.7732638 | 0.0032638 |
| 0.73 | 0.7671335 | 0.0371335 |
| 0.702 | 0.7171009 | 0.0151009 |
| 0.662 | 0.7111704 | 0.0491704 |
| $(\Delta E_1)_{max}$ | | 0.0553762 |

(1) The first model is the GANN model with ordinary parameter settings (choosing parameters without Taguchi method, please see Table 8). This model construction process for GANN could be referred to subsection 5.2, and the estimation process could be referred to subsection 5.3. The estimated output voltages of the six testing data by GANN are shown in Table 9, where $V_G$ is the estimated output voltage of PEMFC from GANN model, $\Delta E_2$ is the absolute error of $V_r - V_G$ and $(\Delta E_2)_{max}$ is the maximal value of $\{\Delta E_2\}$, and the followings are the definitions:

$$\Delta E_2 = |V_r - V_G| \tag{18}$$

$$(\Delta E_2)_{max} = \mathrm{Max}\{\Delta E_2\} \tag{19}$$

(2) The second model is the BPNN model with ordinary parameter settings (please see Table 10 and also refer to Remark 7). The model construction process for BPNN could be referred to subsection 5.2, and the estimation process could be referred to subsection 5.3. The estimated output voltages of the six testing data by BPNN are shown in Table 11, where $V_B$ is the estimated output voltage of PEMFC from BPNN model, $\Delta E_3$ is the absolute error of $V_r - V_B$, and $(\Delta E_3)_{max}$ is the maximal value of $\{\Delta E_3\}$. Both of $(\Delta E_3)$ and $(\Delta E_3)_{max}$ are defined as following:

$$\Delta E_3 = |V_r - V_B| \tag{20}$$

$$(\Delta E_3)_{max} = \mathrm{Max}\{\Delta E_3\} \tag{21}$$

From Tables 7, 9 and 11, it is shown that the constructed GANN model with Taguchi method has a better accuracy than BPNN model and GANN model without using Taguchi method. Therefore, the parameter optimization by Taguchi method for GANN is proven to be useful and effective.

**Table 8 – Parameter settings of GANN model.**

| | | | |
|---|---|---|---|
| Input variables: | 5 | population size($P_S$) | 30 |
| Output variables: | 1 | generation number($G_R$) | 1000 |
| Experimental data samples (for Training): | 200 | crossover rate($C_R$) | 0.7 |
| Value of random number seed: | 0.456 | mutation rate($M_R$) | 0.007 |

**Table 9 – The absolute error and maximal error between the measured and estimated voltages by GANN model.**

| $V_r$ (V) | $V_G$ (V) | $\Delta E_2$ (V) |
|---|---|---|
| 0.838 | 0.670124 | 0.167876 |
| 0.798 | 0.665487 | 0.132513 |
| 0.77 | 0.652321 | 0.117679 |
| 0.73 | 0.636114 | 0.093886 |
| 0.702 | 0.662979 | 0.039021 |
| 0.662 | 0.642553 | 0.019447 |
| $(\Delta E_2)_{max}$ | | 0.167876 |

**Remark 6:** The consideration and reason of factor level selections in Table 1, including Population Size, ($P_S$), Generation number ($G_R$), Crossover Rate ($C_R$), and Mutation Rate ($M_R$), is described as below:

(1) Population Size

The initial population size will have a strong influence for the searching efficiency, and it should depend on the complexity of problems. A larger population has a higher opportunity to obtain the optimal solution, but higher computing power is required and it would be time consuming as well. For a smaller population, it is easier to get stuck into a local optimal solution, and leads to the result of early convergence. Many experts have different opinions about the appropriate population size, and 50 or 100 are acceptable by most of them [33]. To take the convergence and computation time into considerations, we choose the levels to be 40, 60, and 80.

(2) Generation number

Before the start of the program, the generation number has to be determined in advance. When the generation number is reached, the program will be terminated. There is no suggested value for generation number, and it also has to depend on the complexity of problems [24]. In this paper, the complexity is not very high. Thus, the levels are chosen as 100, 150, and 200, by taking into account the convergence and computation time.

(3) Crossover rate

Higher crossover rate will produce the offspring with higher differentiation of chromosomes. However, the chromosome structure of parents is also prone to be broken. On the other hand, lower crossover rate will preserve the original structure of parents, but it requires longer time or generation to obtain

**Table 10 – Parameter settings of BPNN model.**

| | | | |
|---|---|---|---|
| Input variables: | 5 | Neurons of 1st hidden layer: | 11 |
| Output variables: | 1 | Learning rate: | 0.1 |
| Experimental data samples (for Training): | 200 | Momentum factor: | 0.5 |
| Value of random number seed: | 0.456 | | |

**Table 11 – The absolute error and maximal error between the measured and estimated voltages by BPNN model.**

| $V_r$ (V) | $V_B$ (v) | $\Delta E_3$ (V) |
|---|---|---|
| 0.838 | 0.7358351 | 0.1021649 |
| 0.798 | 0.6973217 | 0.1006783 |
| 0.77 | 0.6565605 | 0.1134395 |
| 0.73 | 0.6168661 | 0.1131339 |
| 0.702 | 0.6719822 | 0.0300178 |
| 0.662 | 0.6291916 | 0.0328084 |
| $(\Delta E_3)_{max}$ | | 0.1134395 |

the optimal solution. Many experts have proposed the appropriate crossover rate. Jong and Box [34,35] suggest the crossover rate to be 0.6 and 0.95. In this paper, levels 0.7, 0.8, and 0.9 are determined for verification by Taguchi method.

(4) Mutation rate

Mutation rate is the probability that a chromosome needs to be mutated in a population. That is, the offspring chromosome will not completely inherit from its parents. Instead, some gene or genes of the offspring chromosome could be changed to another value [24]. Until now, there is no consensus for the optimal mutation rate. We just boldly assume the levels to be 0.05, 0.1, and 0.2.

**Remark 7** (please refer to [36]):

(1) Neurons of Hidden Layer

Based on the theorem of a Russian mathematician Kolmogorov, the back propagation network with single hidden layer could handle the mapping from $p$ -dimensional space to $q$ -dimensional space. He proved that $2p + 1$ neurons are required for this hidden layer. In this paper, the hidden layer should have 11 neurons.

(2) Learning rate

The learning rate will influence the convergent speed of a neural network. A higher learning rate would accelerate the convergent process, and a lower learning rate would make it slower. However, there will be negative impact to the neural network training process if the convergent speed is too fast or too slow. A common suggestion for the learning rate is 0.1.

(3) Momentum factor

The momentum factor controls the modification of bias. A good momentum factor could improve the vibration in the convergent process. It can also be initially set with a larger value, and keep decreasing when the training process progresses. The appropriate value for momentum factor is 0.5.

## 6. Conclusion

This paper has presented a new approach to estimate the output voltage of PEMFC accurately by combining the use of a GANN model and the Taguchi method. A Taguchi matrix has been developed to characterize the various control factors for the Taguchi method. Moreover, the experiment results for PEMFC are employed to determine the value of control factors for optimizing on GANN model. Therefore, the objective of reducing estimation error for PEMFC output voltage and reducing the fuel consumption for PEMFC operation can be achieved. Experimental results on the test equipment show that the proposed approach is effective in estimation for the tested PEMFC. This approach also compares the estimation values of output voltage for PEMFC from GANN model without using Taguchi method and BPNN model. One can easily find that the error of the proposed method is much smaller than that of the GANN model without Taguchi method and of the BPNN model; that is, the proposed approach has better performance on estimation for PEMFC output voltage. This approach of combining the GANN model and the Taguchi method has been demonstrated to be successful and the application of this scheme to some complex PEMFC systems will be developed in the future.

## Acknowledgments

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## REFERENCES

[1] Mann RF, Amphlett JC, Hooper MAI, Jensen HM, Peppley BA, Roberge PR. Development and application of a generalized steady-state electrochemical model for a PEM fuel cell. Journal of Power Sources 2000;86:173–80.

[2] Famouri P, Gemmen RS. Electrochemical circuit model of a PEM fuel cell. IEEE Power Engineering Society General Meeting 2003;3:1436–40.

[3] Fricde W, Rael S, Davat B. Mathematical model and characterization of the transient behavior of a PEM fuel cell. IEEE Transactions on Power Electronics 2004;19(16):1234–41.

[4] Pukrushpan JT, Stefanopoulou AG, Peng H. Modeling and control for PEM fuel cell stack system. IEEE Control Systems Magazine 2004;4(13):30–46.

[5] Correa JM, Farret FA, Canha LN. An analysis of the dynamic performance of proton exchange membrane fuel cells using an electrochemical model. The 27th Annual Conference of IEEE Industrial Electronics Society. 2001; 1: p. 141–146.

[6] Larminie J, Dicks A. Fuel cell systems explained. 2nd ed. John Wiley & Sons; 2003.

[7] Lee WY, Park GG, Yang TH, Yoon YG, Kim CS. Empirical modeling of polymer electrolyte membrane fuel cell performance using artificial neural networks. International Journal of Hydrogen Energy 2004;29:961–6.

[8] Youssef ME, Khalil MH, Khairia EAN. Neural network modeling for proton exchange membrane fuel cell (PEMFC). Advances in Information Sciences and Service Sciences 2010; 2(11):61–6.

[9] Rezazadeh A, Sedighizadeh M, Karimi M. Proton exchange membrane fuel cell control using a predictive control based on neural network. International Journal of Computer and Electrical Engineering 2010;2(11):81–5.

[10] Jemeï S, Hissel D, Péra MC, Kauffmann JM. A new modeling approach of embedded fuel-cell power generators based on

artificial neural network. IEEE Transaction on Industrial Electronics 2008;55:437–47.
[11] Jemei S, Harel F, Francois X, Candusso D, Hissel D, Pera MC and et al. PEM fuel cell modelization including durability considerations. In: 2005 IEEE ISIE. June 20–23, 2005, Dubrovnik, Croatia.
[12] Sedighizadeh M, Rezazadeh A. A neuro adaptive control strategy for movable power source of proton exchange membrane fuel cell using wavelets. World Academy of Science, Engineering and Technology 2007;36:285–9.
[13] Fowlkes WY, Creveling CM. Engineering methods for robust product design: using Taguchi methods in technology and product development. Reading. MA: Addison-Wesley; 1995.
[14] Hedayat AS, Sloane NJA, Stufken J. Orthogonal arrays: theory and applications. New York: Springer; 1999.
[15] Lochner RH, Matar JE. Designing for quality: an introduction to the best of Taguchi and western methods of statistical experimental design. Milwaukee: WI: ASQC Quality; 1990.
[16] Ross PJ. Taguchi techniques for quality engineering. 2nd ed. McGraw-Hill; 1995.
[17] Kaytakoğlu S, Akyalçın L. Optimization of parametric performance of a PEMFC. International Journal of Hydrogen Energy 2007;32:4418–23.
[18] Lo YL, Tsao CC. Integrated Taguchi method and neural network analysis of physical profiling in the wirebonding process. IEEE Transactions on Components and Packaging Technologies 2002;25:270–7.
[19] Maxwell GM, MacLeod C. Using Taguchi methods to train artificial neural networks in pattern recognition, control and evolutionary applications. Proceedings of the 9th International Conference on neural information processing, 2002. p. 301–305.
[20] Chang KY, Lin HJ, Chen PC. The optimal performance estimation for an unknown PEMFC based on the Taguchi method and a generic numerical PEMFC model. International Journal of Hydrogen Energy 2009;34:1990–8.
[21] Abrahart R, Kneale PE, See LM. Neural networks for hydrological modeling. Taylor & Francis; 2004.
[22] Haykin S. Neural networks: A comprehensive foundation. Prentice Hall; 1999.
[23] Wasserman PD. Neural computing theory and practice. New York: Van Nostrand Reinhold; 1989.
[24] Goldberg DE. Genetic algorithms in search, optimization, and machine learning. Addison-Wesley; 1989.
[25] Omekanda AM., Robust torque- and torque-per-inertia optimization of a switched reluctance motor using the Taguchi methods. IEEE International Conference on Electric Machines and Drives, 2005. p. 521–526.
[26] Lin RM, Li JC, Nee TE. Brightness improvement and limited forward voltage of the AlGaInP MQW LED with Wet-Oxidation by Taguchi method. IEEE Conference on Emerging Technologies - Nanoelectronics, 2006, p. 245–248.
[27] Unal R, Stanley DO, Joyner CR. Propulsion system design optimization using the Taguchi method. IEEE Transactions on Engineering Management 1993;40:315–22.
[28] Box GEP, Hunter WG, Hunter JS. Statistics for experimenters. an introduction to design, data analysis, and model building. John Wiley & Sons; 1978.
[29] Montgomery DC. Design and analysis of experiments. New York: Wiley; 1991.
[30] Phadke MS. Quality engineering using robust design. NJ: Prentice-Hall; 1989.
[31] Park SH. Robust design and analysis for quality engineering. London, U.K: Chapman & Hall; 1996.
[32] Taguchi G, Chowdhury S, Wu Y. Taguchi's quality engineering handbook. Wiley-Interscience; 2004.
[33] Reeves CR. Genetic algorithms for the operations researcher. IMFORMS Journal on Computing 1997;9:231–50.
[34] Jong KAD., An analysis of the behavior of a class of genetic adaptive systems. Doctoral dissertation, University of Michigan, Ann Arbor, MI.; 1975.
[35] Grefenstette JJ. Optimization of control parameters for genetic algorithms. IEEE Transactions on Systems, Man and Cybernetics; 1986:122–8. SMC-16P.
[36] Hagan MT, Demuth HB, Beale MH. Neural network design. Thomson Learning; 1996.