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NEURAL NETWORK MODEL OF POLYMER ELECTROLYTE MEMBRAN FUEL CELL FOR ELECTRICAL VEHICLE

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ABSTRACT

This paper presents Neural Network (NN) model of Polymer Electrolyte Membran (PEM) Fuel Cell for electric vehicle. The NN model simplifies the conventional model that considered thermodynamics, electrochemistry, hydrodynamics and mass transfer theory. The NN has a multilayer feed forward network structure and is trained using a back propagation learning rule. The NN model is used to predict the stack voltage of a PEM fuel cell to the vehicle speed. The data for the training of the NN model uses the parametric data that developed from the vehicle model and the PEM fuel cell model. The simulation results have shown that NN model can successfully predict the stack voltage to the vehicle speed. The performance of the network meets the requirement at epoch 50 and the error is 0.000000338.

Keywords: *Neural network, Proton exchange membrane fuel cell (PEMFC), Back-propagation (BP), Vehicle model*

1. INTRODUCTION

A fuel cell is a source of electrical energy using hydrogen and oxygen to generate electricity. This technology uses hydrogen as fuel and oxygen as oxidant. Output of fuel cells are heat and water that don't pollute the environment. A single cell consists of an electrolyte in contact with an anode and a cathode on either side. The most common classification of fuel cells is by the type of electrolyte used in the cells. One of the type is Polymer Electrolyte Membrane or Proton Exchange Membrane Fuel Cell (PEM Fuel Cell)[1]. Development of this alternative energy is very important because it has a number of advantages [2].

- Fuel cells have higher efficiency than combustion engines whether piston or turbine based.
- Fuel cells are very simple. They have no moving parts. Its reliability is high and they can be loaded in a long time.
- The product of the fuel cells are heat and water then they generate zero emission. Fuel cells are suitable used in vehicles, as there is a requirement to reduce vehicle emissions, and even eliminate them.

Fuel cells are very quiet, which may make them attractive for a variety of applications, such as portable power, backup power, and military applications.

Fuel cells can be utilized in a construction of portable electronic equipment, vehicles, residential or even in distributed power systems [3]. PEM fuel cells have the advantage when compared with wind and photovoltaic generation. They can be placed at any site in a distribution system, without geographic limitations, to achieve the best performance. Electric vehicles are another major application of PEM fuel cells. The increased desire for vehicles with less emission has made PEM fuel cells attractive for vehicular applications since they emit essentially no pollutants and have high-power density and quick start [4].

A number of approaches have been used to model PEM fuel cells behaviour. A parametric model of PEM fuel cell developed by Amphlett using a mechanistic approach [5] and by Wang using electrical circuits [4]. The operating principles of PEM fuel cells involve some theories, such as thermodynamics, electrochemistry, hydrodynamics and mass transfer theory. These theories comprise a complex nonlinear system, for

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which it is difficult to establish a mathematical model [6].

Artificial neural networks (ANNs) have widened covering such endeavours of life such as medicine, finance and unsurprisingly engineering (diagnostics of faults in machines). ANNs have been described as diagrammatic representation of a mathematical equation that receives values (inputs) and gives out results (outputs) [7]. The ANNs have a multilayer feed forward network structure and are trained using a back propagation learning rule. They can be applied to linear and non-linear problem domains.

In this paper, application of ANN is used to predict the stack voltage of a PEM fuel cells. In this analysis, two parameters namely stack current and stack temperature were used as input to the network with the stack voltage being the only output. Stack current for the network input developed from vehicle model. In our study, inputs of vehicle model are vehicle speed, acceleration and slope of the road and output of vehicle model is the required current of electric motor. This current is used as input to the NN model of PEM fuel cells. In order to train the NN model uses a back propagation algorithm.

2. MATHEMATICAL MODEL

Mathematical models were developed to investigate performances of electric vehicle and PEM fuel cell. The proposed system is shown in Figure 1. The proposed system model consists of vehicle model and PEM fuel cell model. In this study, the PEM fuel cell model is replaced by the neural network model.

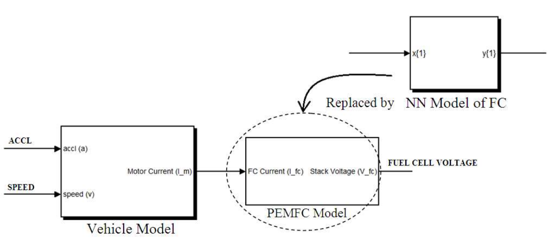

Figure 1. Proposed System Model

2.1 Vehicle Model

This vehicle model is used to calculate the continuous power requirement from electric motor of vehicle [8] [9]. The required power (P_{in}) of electric motor is equel total power that should be transferred to the wheels (P_{tot}) divided by the efficiency of the motor (η).

$$P_{in} = \frac{P_{tot}}{\eta} \qquad (1)$$

Total power that should be transferred to the wheels is obtained by multiplying the total force(F_{tot}) and vehicle speed (v).

$$P_{tot} = F_{tot} \times v \qquad (2)$$

The selected electric motor has to overcome several forces, which are wheel friction force (F_{wf}), air friction force (F_{af}), slope friction force (F_{sf}) and acceleration force (F_a). Total force (F_{tot}) is sum of wheel friction force, air friction force, slope friction force and acceleration force, as follow:

$$F_{tot} = F_{wf} + F_{af} + F_{sf} + F_a \qquad (3)$$

Wheel friction force (F_{wf}) is caused by the friction of tires on the road. Wheel friction force is constant, and almost does not depend on the speed of the vehicle. This force is proportional to the weight of the vehicle (m), acceleration due to gravity (g) and the coefficient of wheel friction (C_{rr}) by the following equation:

$$F_{wf} = C_{rr}.m.g \qquad (4)$$

Slope friction force (F_{sf}) is force on the vehicle to move up or move upward with slope (ψ). Slope friction force is expressed as:

$$F_{sf} = m\, g \sin\psi \qquad (5)$$

Air friction force (F_{af}) is due to the friction of the vehicle body moving through the air. This force is determined by shape of the surface of the vehicle (A_f), coefficient of form (C_d), vehicle speed (v), and air density (ρ). This formula for this component is:

$$F_{af} = 0{,}5\, C_d\, \rho\, A_f\, v^2 \qquad (6)$$

Acceleration force (F_a) is required to increase the speed of vehicle. If the linier acceleration (a) of vehicle according to Newton's second law, is:

$$F_a = m\, a \qquad (7)$$

Static model for vehicle has been built in Matlab/Simulink, based on equation (1) to (7). The required power of electric motor, which is a function of vehicle speed, acceleration and slope of the road, can be obtained from the model. Figure 2 shows the block diagram, based on which the Matlab/Simulink model has been built. In this

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figure, the input quantities are vehicle speed, acceleration, slope of the road and the output quantity is the required power of electric motor (P_i). The current of electric motor (I_m) that used to the input of fuel cell model is given by

$$I_m = \frac{P_i}{V_{stack}} \quad (8)$$

where V_{stack} is the stack voltage of the PEM fuel cell.

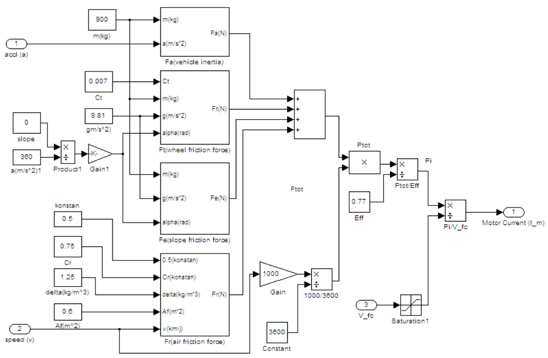

Figure 2. vehicle model built

2.2 PEM Fuel Cell Model

The output voltage (V_{cell}) of a single cell of PEM fuel cell could be found using Eq.9 [1][10]. When a cell delivers to the load, the no-load voltage is reduced by the voltage losses. The voltage losses are activation, ohmic and concentration voltage losses.

$$V_{cell} = E_{cell} - V_{act,cell} - V_{ohm,cell} - V_{con,cell} \quad (9)$$

E_{cell} = It is the theoretical value of the open-circuit voltage of a hydrogen fuel cell, a typical value is 1,229V.

$V_{act,cell}$ = This voltage drop is caused by the slow-ness of the reactions taking place on the surface of the electrodes, is known as activation losses.

$V_{ohm,cell}$ = This voltage drop is the straightforward resistance to the flow of electrons through the materials of the electrodes and the various interconnections, is known as ohmic losses.

$V_{con,cell}$ = each part of the cell voltage drop due to diffusion of the reactants (H_2, O_2) into the electrolyte and release of products (H_2O) out of the cell, is known as concentration voltage losses.

If all the cells are in series, stack output is the product of a single cell voltage and number of cells in the stack (n).

$$V_{stack} = V_{cell} \text{ x } n \quad (10)$$

Using equations given in (9) (10), the fuel-cell output voltage was modeled and given in Figure 3. In this figure, the input quantities are anode and cathode pressures, initial temperature of the fuel cell, and room temperature. At any given electric motor current, the internal temperature is determined and both the electric motor current and temperature are fed back to different blocks, which take part in the calculation of the fuel-cell output voltage.

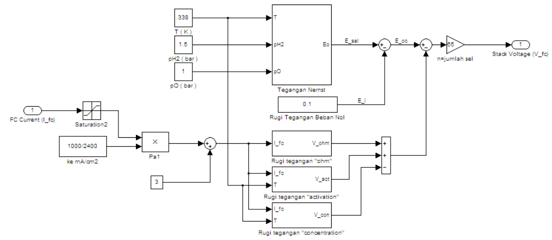

Figure 3. Diagram of building a static model of PEM fuel cell in SIMULINK.

3. NEURAL NETWORK MODEL OF THE PEM FUEL CELL

Artificial neural networks are models that process information in a similar way to a biology of the brain. Their basic unit is the artificial neuron. A neural network is composed of neurons. The network function is determined by the connections between the neurons. Structure of the network is shown in Figure 4. The neuron processes numerical information from input nodes, and gives out an output [7].

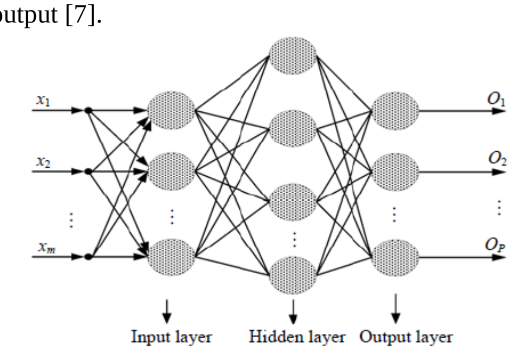

Figure 4. Neural Network Structure

A neural network consists of three main parts [6].

- The first part is the input layer. It processes the input data to product the next layer. The x_1, x_2, …, x_m denote the inputs of the network.
- The second part is hidden layers. Neural networks usually have one or more hidden layers that consist of neurons with nonlinear sigmoid transfer function. The hidden layers process from the input layer and produce an

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output that will be sent to the third layer. The $y_1, y_2, \ldots, y_r$ denote the hidden units.

- The third part is the output layer. The output layer represents the output of ANN to the real world. The $O_1, O_2, \ldots, O_P$ denote the outputs of the hidden layer units.

The output of each of the previous layer is used as the input of the next layer. Each neuron in the previous layer is connected with all neurons in the next layer. The connections between the units of different layers are called weight and bias. Input and output layers are directly accessible while the hidden layers are not.

The models have been developed using feed-forward neural network with the back propagation (BP) algorithm. In order to train the neural network, the input and the output training data are needed. The output training data is referred to as the target output of the neural network. Training of the neural network would be executed until the output of neural network more nearly or equal target. The difference between the network output (O_k) and the desired target (t_k) is called the error (E_p). For this purpose, the value of the error must be minimized. The error of the network training can be calculated as following:

$$E_p = \frac{1}{2}\sum_{i}^{N}(t_k - O_k)^2 \tag{11}$$

P is the total number of training pairs included in the training data set and N is the number of the neural network outputs [6].

Each neuron of the layer produces an output. The output of the z_j hidden layer unit is given by

$$z_j = f(v_{j0} + \sum_{i=1}^{n} w_{ji} x_i) \tag{12}$$

where is f is the activation function, x_i is the ith input, w_{ji} is the weight of connection from ith input unit to the jth hidden layer unit, and v_{j0} is the bias value of the jth hidden layer unit. And the output (O_k) of the output layer is given by

$$O_k = f(v_{k0} + \sum_{j=1}^{p} z_j \cdot w_{kj}) \tag{13}$$

where w_{kj} is the strength of the connection from the hidden layer unit to the output unit, and v_{k0} is the bias value of output unit.

The BP network learning method is to make the error function down the direction of the negative gradient for correcting the weight and bias of the network. The change in weight Δw_{ji} is based on the gradient descent and is given by

$$\Delta w_{ji} = -\eta \frac{\partial E}{\partial w_{ji}} \tag{14}$$

where η is the learning rate. The value of the learning rate is between 0 and 1.

NN model using a back propagation algorithm, consists of three phase as follow:

1. Forward phase
   In this phase, calculates the output signal from the input layer to the output layer using a specific activation function. Input signals (x_i) are propagated to the hidden layer units (z_j) with a specific activation function using Eq.(12). The outputs of hidden layer unit are then propagated forward again to the hidden layer units on it with the specified activation function until produce the network output (O_k) using Eq.(13) .
2. Back phase
   In the second phase, calculates the error between the desired targets (t_k) and the network output using Eq.(11). If the error is smaller than the tolerance limit, then iteration is stopped. If the error is still greater than the tolerance limit, then weights of the network will be modified to reduce the errors. Based on the error, is calculated the factor δ_k that is used to change the line weights that relate directly to the hidden layer and output layer. The change in weight is calculated using Eq.(14).
3. Repair (improvement) phase of the weights.
   After all factors δ_k are calculated, the weights of all lines simultaneously modified. The changes in weights Δw_{ij} of a line are determined by the factors δ_k. The new weights of a line is given by

   $$w_{ji}(n+1) = w_{ji}(n) + \Delta w_{ji} \tag{15}$$

Phases 1 to 3 is repeated until termination conditions are met. Termination conditions are often used, are the number of iterations or the goal error.

4. RESULT AND DISCUSSION

Since the data on operating PEM fuel cell is not available at the present, a parametric equation developed from the proposed system model that consist of the vehicle model and the PEM fuel cell model. The vehicle model is used to find electric current of the vehicle motor. Figure 5 shows the

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simulation result of the vehicle model with input driving cycle from Figure 7.

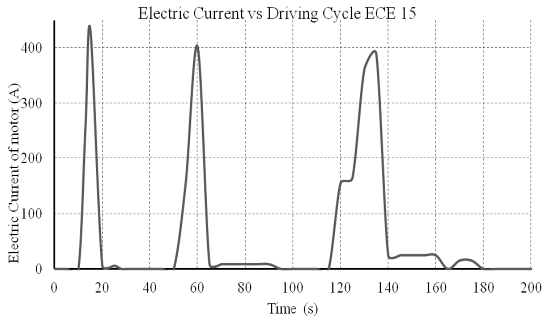

Figure 5. Electric Current Of The Vehicle Motor

The PEM fuel cell model was tested in comparison with data from the matlab fuel cell model. This model needs the stack current as input data and products the stack voltage as output data. Simulation result can be seen in Figure 6. The error between the two models are 1.56%.

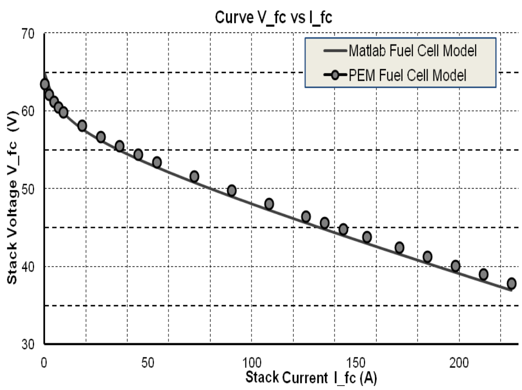

Figure 6. Fuel Cell Polarization Curve

The next simulation determines the training data of the NN model. Data from the vehicle model and the PEM fuel cell model are used to generate the data required for the training of the NN model using Matlab/Simulink. The input data for vehicle model is vehicle speed, as is shown in Figure 7. The required output data from PEM fuel cell model is stack voltage. In the training process, the generated data are divided into three parts [11] [12]:

- training data is approximately 60% of the total data
- validation data is 20% of the training data and 20% of the total data,
- test data is 20% of the total data instead of training data.

Activation function used in the training is tansig (bipolar sigmoid), is given by $f(\mathrm{net}) = \frac{2}{1+e^{-\mathrm{net}}} - 1$.

In the setting of the program, the goal error is 0.00001 and the maximum iteration is 3000.

The stack voltage is generated by Neural Network model, as can be seen in Figure 8. In this figure, the generated data of the NN model shows good consistency with the referenced model (PEM Fuel Cell Model). The concordance between both models is clear. At high speeds, the stack voltages decrease. The stack voltages of the ANN have matched with the desired target.

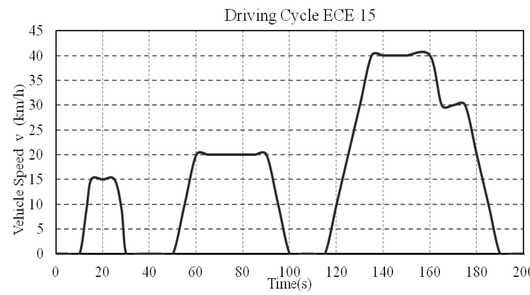

Figure 7. Driving Cycle ECE15 For The Input Data Of Vehicle Model

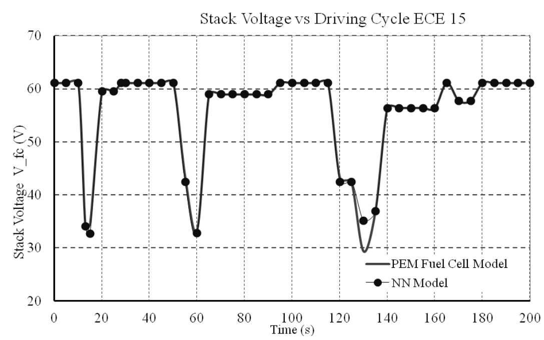

Figure 8. Stack Voltage Vs Vehicle Speed

Figure 9 shows that the performance of the network meets the requirement at epoch 50. The value of error is 0.000000338 less than the goal error of 0.00001.

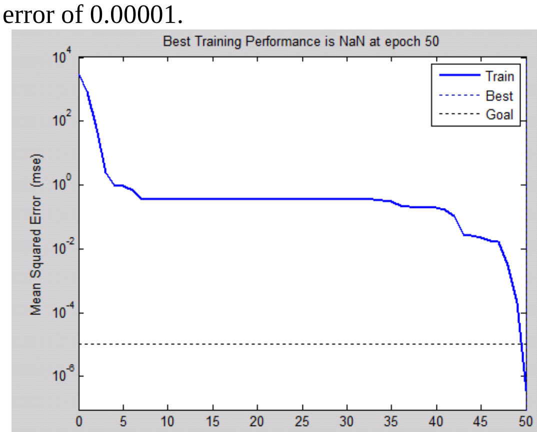

Figure 9. Learning Error Of BP Algorithm

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5. CONCLUSION

In this paper the NN model of PEM fuel cell using Matlab/Simulink is presented. The model is used to predict the stack voltage to the vehicle speed. The speed of vehicle in this study uses Driving Cycle ECE15. The PEM fuel cell model based on an artificial neural network shows a good agreement with the referenced model. The resulting configuration of the NN model is 2 units of input layer, 1 unit of the hidden layer with 24 neurons and 1 unit of output layer.

In the next experiment, data from the experiment set up could be trained to NN model. It is used to predict the stack voltage with good precision and the need for extensive experiments.

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