



# NEURAL NETWORK BASED PEM FUEL CELL MODELING FOR ELECTRIC VEHICULAR APPLICATION

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## ABSTRACT

Analysis and performance of electric vehicle fed with fuel cell requires a modelling of fuel cell. This modeling of fuel cell with driving pattern is not easy to achieve. This paper deals with neural network trained fuel cell for driving pattern of electric vehicles. With this pattern the trained output voltage and power of the fuel cell can be decided. The multi-layer perceptron neural network is used to predict the output voltage and power of the PEM fuel cell. The modelling and simulation work is carried using Matlab/Simulink in order to verify the reliability of the electric vehicle performance by applying three different modified standard driving cycles (M-NEDC/ M-UDDS/M-US06). The simulation results have shown that NN model can successfully predict the stack voltage and power with the correlation of 0.9999.

**Keywords:** Neural Network, Multi-Layer Perceptron, Drive Cycle, Mean Square Error.

## I. 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 is 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].

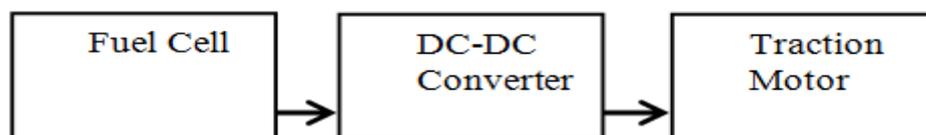
A number of approaches have been used to model PEM fuel cells behavior. A parametric model of PEM fuel cell developed by Amphlett using a mechanistic approach [5] and by Wang using electrical circuits [4]. The operating principles of PEM fuel cells involve some theories, such as thermodynamics, electrochemistry, hydrodynamics and mass transfer theory. These theories comprise a complex nonlinear system, for which it is difficult to establish a mathematical model [6].

Artificial neural networks (ANNs) have widened covering such endeavors 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 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.

## **II. PEM FUEL CELL DRIVEN ELECTRIC VEHICLE**

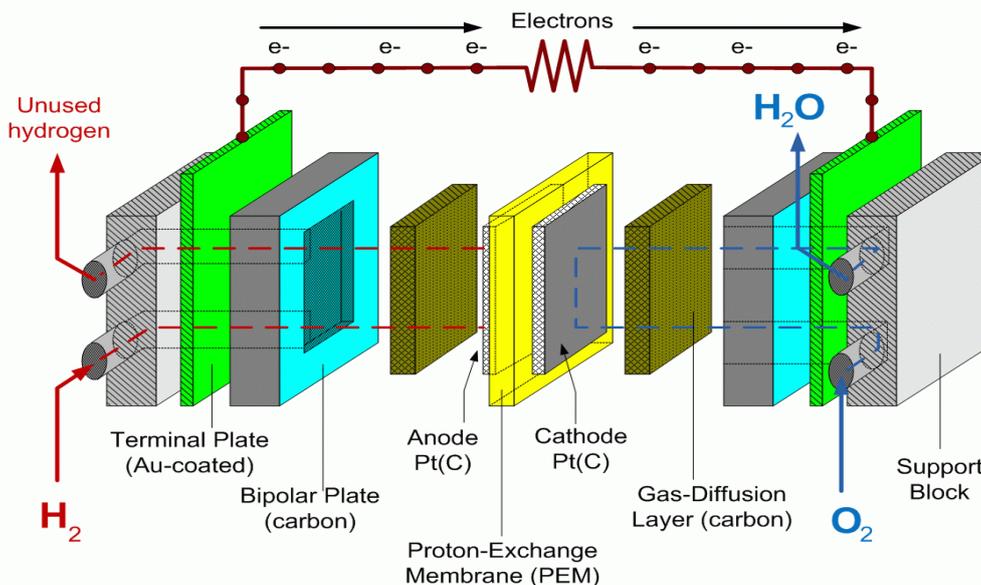
Fuel cell driven electric vehicle modelling is started with the development of the fuel cell stack that includes fuel cell stack sizing and polarization dynamics for standalone fuel cell. A single fuel cell is not able to provide the nominal power required to meet the load. Hence the required number of fuel cells is connected in series to form the fuel cell stack that yield nominal voltage and power to propel the electric vehicle. The output of the fuel cell stack can be unregulated output voltage which cannot be connected directly with the dynamics module. The vehicle dynamics module requires always constant power for the propulsion of electric vehicle. Hence there is a need for converter circuit to convert the unregulated output voltage into regulated voltage. The required output voltage from the converter unit propagates towards the vehicle dynamics module to provide the power to the wheel. The complete model of the proposed electric vehicle module is shown in the figure. 1.



**Figure 1 Fuel Cell Driven Electric Vehicle Model**

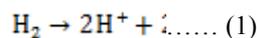
### **2.1 Pem fuel cell**

Proton Exchange membrane fuel cells, also known as polymer electrolyte membrane fuel cells (PEMFC), are the type of fuel cell developed for transport application as well as for stationary fuel cell application. PEMFCS are built out of membrane electrode assemblies (MEA) which includethe electrodes, eletrolyte, catalyst and gas diffusion layers as shown in the figure. 2.

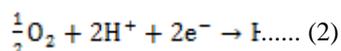


**Figure 2 Proton exchange membrane fuel cell**

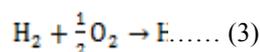
A proton exchange membrane fuel cell transforms the chemical energy liberated during the electrochemical reaction of hydrogen and oxygen to electrical energy. A stream of hydrogen is delivered to anode, at the anode side it is catalytically split into proton and electrons given in the equation (1)



The newly formed protons permeate through the polymer electrolyte membrane to the cathode side. The electron travel along an external load circuit to the cathode side of the MEA, thus creating the current output of the fuel cell. Meanwhile, a stream of oxygen is delivered to the cathode side of MEA. At the cathode side oxygen molecules react with the protons permeating through the polymer electrolyte membrane and the electrons arriving through the external circuit to form water molecules given in the equation (2).

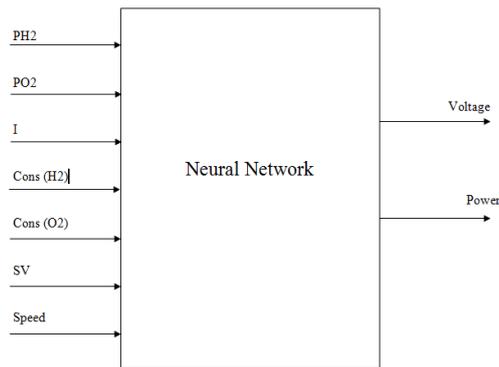


Overall reaction given in the equation (3)



## 2.2 Pem fuel cell modeling

The performance of the fuel cell stack system is highly affected by the various polarization losses and also various electrochemical, thermodynamic and thermal processes takes place inside the fuel cell which makes the system to behave highly non-linear. Hence it is very difficult to perform mathematical modelling. Therefore neural network approach is used to overcome the complexity in the conventional mathematical modeling [13]. The input parameters chosen for the neural network are current density, partial pressure of hydrogen, oxygen, consumption of hydrogen, oxygen, stack efficiency and speed and the outputs from the network are stack voltage and power. The neural network with the defined inputs and outputs is shown in the figure 3.



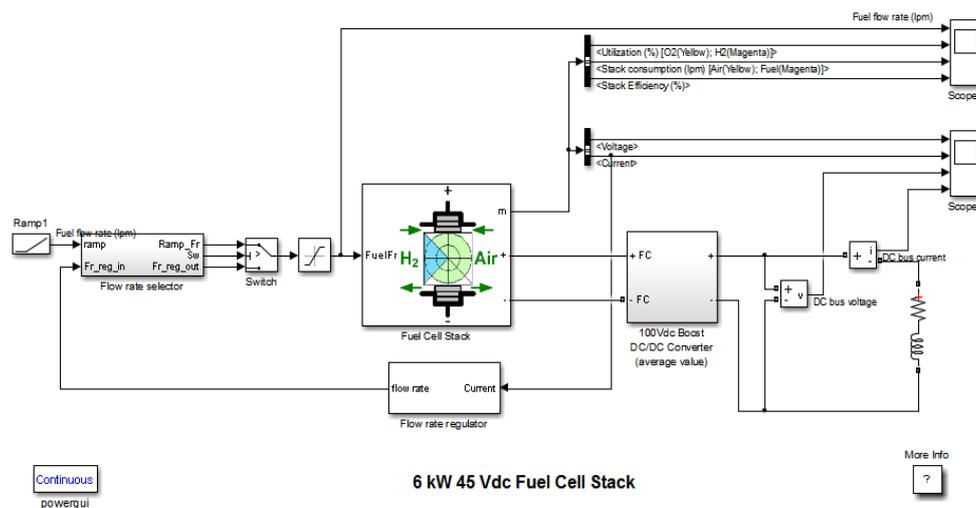
**Figure 3. Input-Output parameter set**

The specifications of the proposed fuel cell are given in the Table 1, which describes the number of fuel cells in a stack, maximum power output (KW), nominal cell voltage (V), nominal stack voltage (V), fuel supply pressure (bar) and air supply pressure (bar).

**Table 1 Fuel cell parameters**

SL No	Parameters	Specifications
1	Number of fuel cells in stack	65
2	Maximum power output (KW)	6
3	Nominal cell voltage (V)	0.6923
4	Nominal stack voltage (V)	45
5	Fuel supply pressure (bar)	1.5
6	Air supply pressure (bar)	1

The data required to train the neural network is generated from the simulation model of Ballard 6KW PEM fuel cell developed in MATLAB/SIMULINK environment [5] which is shown in the figure 4. Speed data is taken from the Drive cycle patterns.



**Figure 4 Ballard 6KW PEM Fuel Cell**

### 2.3 Multi-Layer Perceptron Neural Network

A multi-layer perceptron (MLP) is feed forward artificial neural network model that maps sets of input data onto a set of appropriate outputs. An MLP consists of multi layers of nodes in directed graphs, with each layer fully connected to the next one. Except for the input nodes, each node is a neuron (or processing element) with a nonlinear activation function. MLP utilizes a supervised learning technique called back propagation for the training the network. MLP is a modification of the standard linear perceptron and can distinguish data that are not linearly separable. MLP network architecture is shown in the figure 5.

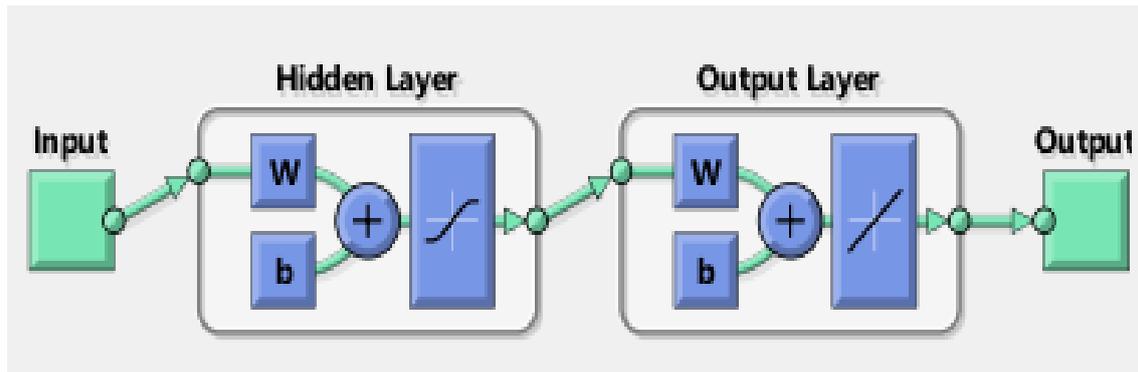


Figure 5 MLP Neural Network Architecture

#### Activation Function

If a multilayer perceptron has a linear activation function in all neurons, that maps the weighted inputs to the output of each neuron, then it is easily proven with linear algebra that any number of layers can be reduced to the standard two layer input-output model. What makes a multilayer perceptron different is that some neurons use a nonlinear activation function which was developed to model the frequency of action potentials, or firing, of biological neurons in the brain. This function is modelled in several ways. Since the input range is normalized in between [-1, 1]. Hence the activation function used in this paper is tangential sigmoidal (tansig) equations given in the equation (4).

$$Y_j(X) = \tanh(G_j(X)) = \frac{e^{G_j(X)} - e^{-G}}{e^{G_j(X)} + e^{-G}} \dots \dots (4)$$

### III. RESULT AND DISCUSSION

The simulation work is carried by using MATLAB/SIMULINK to verify the reliability of PEMFC model performance by applying a modified drive cycle pattern(M-UDDS, M-NEDC, M-US06) as the input. The performance of the proposed MLP network in terms of performance indices such as mean squared error (MSE), Regression analysis, epoch and number of neurons in the hidden layer is analysed. The Levenberg-Marquardt training algorithm for the optimum training of the neural network. By varying the hidden neurons from 1 to 15, it is observed that with 10 hidden neurons we will get the less MSE and yields good prediction performance with minimum MSE value of  $7.7223 \times 10^{-08}$  with 1000 epochs and the response of the MLP network is shown in the figure 6.

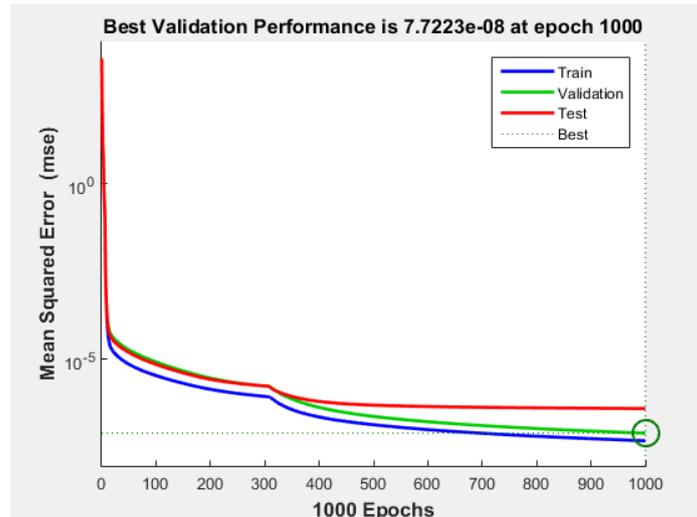


Figure 6 Response of the MLP network

Table 2 shows the training results of the training algorithm attained using MLP network with 10 neurons in a hidden layer having regression of 0.9999 with iteration rate of 1000.

Table 2 Training result of 10 hidden neuron in a layer.

Performance Measure	Hidden Neurons
MSE	7.7223*e <sup>-08</sup>
Regression	0.9999
Iteration	1000

The obtained neural network block is connected to the Ballard PEM fuel cell to check the correctness in the output obtaining from the neural network block. The figure 7 shows the simulation of neural network connected to the fuel cell mathematical model. The simulation is made to run for 120seconds.

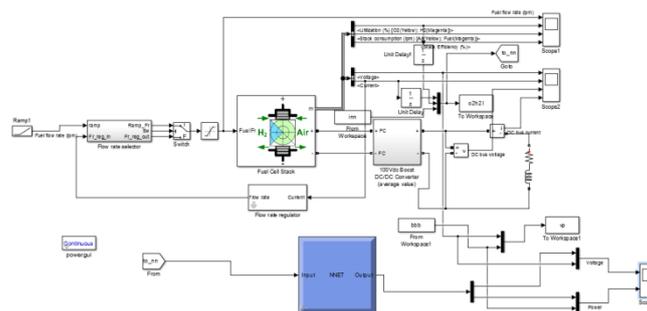
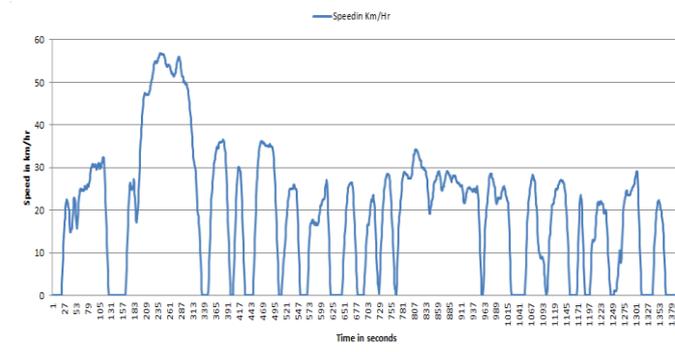


Figure 7 Neural network imparted to the mathematical model

For the derived NN model, the drive cycle pattern such as M-UDDS, M-NEDC, M-US06 which as the speed data are fed as the external input to the NN model and its output voltage and power is estimated

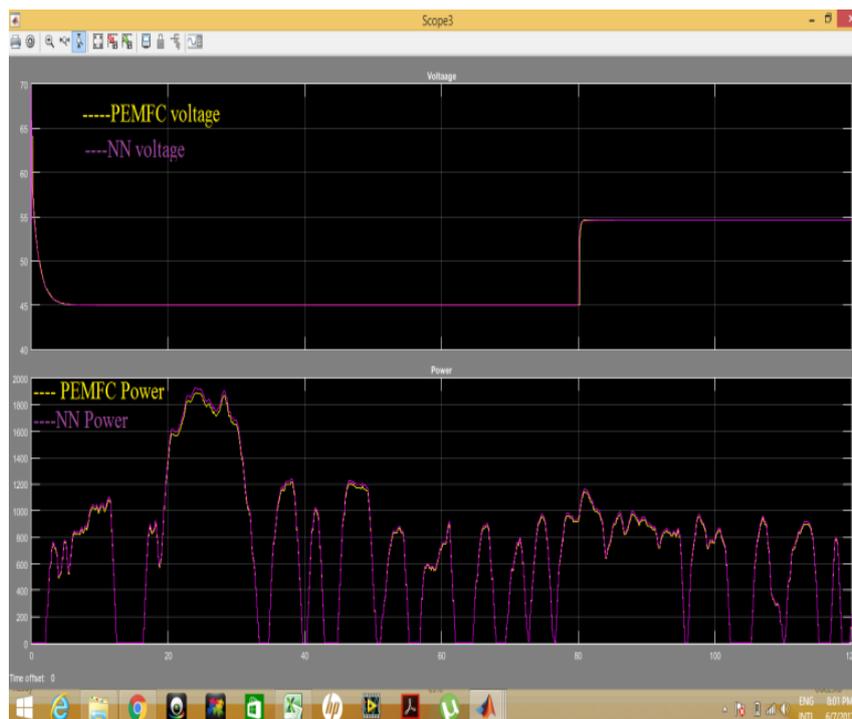
**M-UDDS**

The modified urban dynamometer driving schedule (M-UDDS) drive cycle pattern for the analysis of the developed vehicle model with the speed of the vehicle is shown in the figure 8. This M-UDDS drive cycle is used to simulate the urban/city driving of the vehicle that provides frequent start and stops.



**Figure 8 M-UDDS drive cycle pattern**

The comparison between the required vehicle power and the available power from the energy source with the M-UDDS drive cycle pattern is shown in the figure 9, which clearly indicates that the developed neural network model is providing a required voltage and power as the fuel cell generates.



**Figure 9 Output voltage and power waveform for M-UDDS**

**M-NEDC**

The modified New European driving cycle drive cycle pattern (M-NEDC) for the analysis of the developed vehicle model is shown in the figure 10. The M-NEDC drive cycle with maximum speed range of 120km/hr is used to analyse the power behaviour of the model.

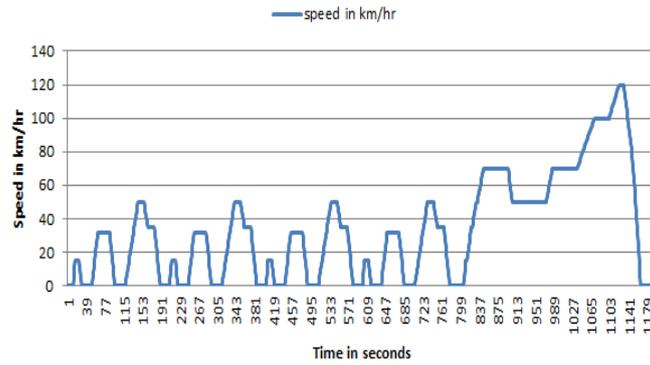


Figure 10 M-NEDC drive cycle pattern

This drive cycle pattern is given to the system and comparison between the required vehicle power and available power from the source with the M-NEDC drive cycle pattern is shown in the figure 11, which clearly indicates that the developed neural network model is providing a required voltage and power as the fuel cell generates.

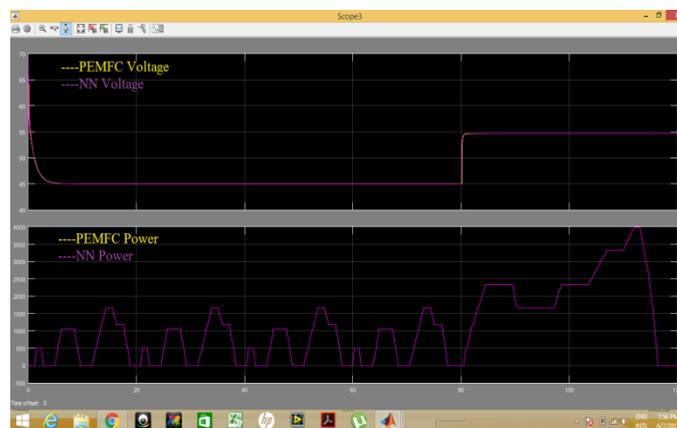


Figure 11 Output voltage and power waveform for M-NEDC

**M-US06**

The M-US06 is a high acceleration aggressive driving schedule that is often identified as the “Supplemental Federal Test Procedure” driving schedule. The M-US06 drive cycle pattern for the analysis of the developed vehicle model is shown in figure 12.

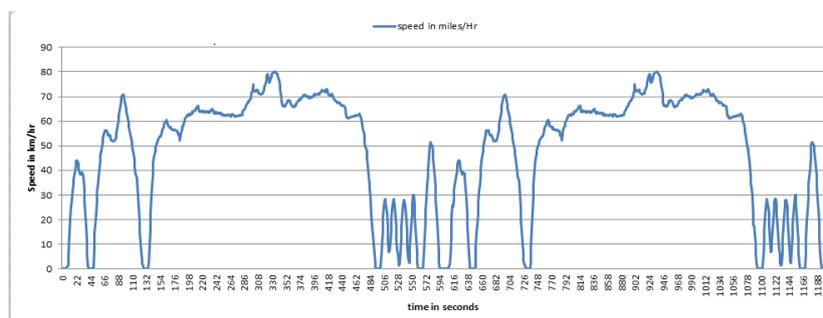


Figure 12 M-US06 Drive cycle pattern

The comparison between the required vehicle power and the power delivered by the energy source with the M-US06 drive cycle is shown in the figure 13, which clearly indicates that the developed neural network model is providing a required voltage and power as the fuel cell generates.

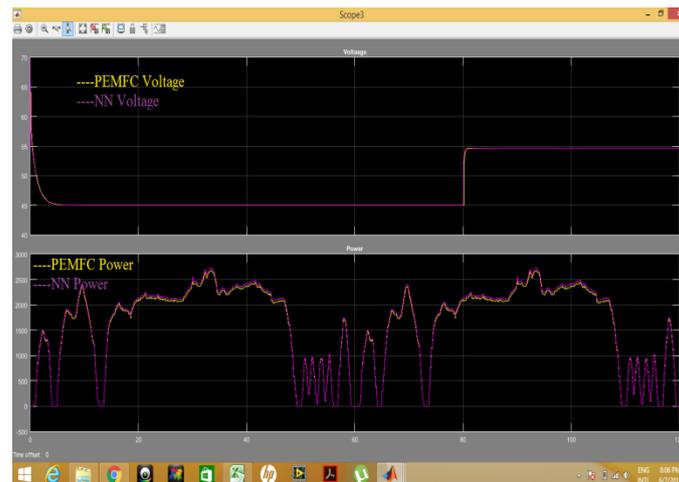


Figure 13 Output voltage and power waveform for M-US06

#### IV. CONCLUSION

Artificial Neural Network technique defeats the complexity in developing mathematical model of the fuel cell. The Multi-Layer Perceptron neural network technique is used in the estimation of the stack voltage and power of the PEM Fuel cell model. The modelling and simulation work is carried using Matlab/Simulink in order to verify the reliability of the electric vehicle by using the different drive cycle patterns such as M-UDDS, M-NEDC, M-US06. The waveform shown in the figure 9, 11, 13 shows that the result obtained from the neural network such as voltage and power follows the exact path of the PEM fuel cell module with the correlation of 0.9999 with the mean square error of  $7.7223 \times 10^{-8}$ .

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