Modeling of PEM Fuel Cell Stack System using Feed-forward and Recurrent Neural Networks for Automotive Applications

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Abstract— Artificial Neural Network (ANN) has become a significant modeling tool for predicting the performance of complex systems that provide appropriate mapping between input-output variables without acquiring any empirical relationship due to the intrinsic properties. This paper is focussed towards the modeling of Proton Exchange Membrane (PEM) Fuel Cell system using Artificial Neural Networks especially for automotive applications. Three different neural networks such as Static Feed Forward Network (SFFN), Cascaded Feed Forward Network (CFFN) & Fully Connected Dynamic Recurrent Network (FCRN) are discussed in this paper for modeling the PEM Fuel Cell System. The numerical analysis is carried out between the three Neural Network architectures for predicting the output performance of the PEM Fuel Cell. The performance of the proposed Networks is evaluated using various error criteria such as Mean Square Error, Mean Absolute Percentage Error, Mean Absolute Error, Coefficient of correlation and Iteration Values. The optimum network with high performance indices (low prediction error values and iteration values) can be used as an ancillary model in developing the PEM Fuel Cell powered vehicle system. The development of the fuel cell driven vehicle model also incorporates the modeling of DC-DC Power Converter and Vehicle Dynamics. Finally the Performance of the Electric vehicle model is analyzed for two different drive cycle such as M-NEDC & M-UDDS.

Keywords-PEM Fuel Cell, Static Feed Forward Network (SFFN), Cascaded Feed Forward Network (CFFN), Fully Connected Dynamic Recurrent Network (FCRN), Drive cycle

I. INTRODUCTION

The Statistical analysis with the current rate of discovery of new oil reserves and the current consumption rate reports that the world oil reserve will be depleted by 2049 [1]. The vehicle sector is the most promising and emerging one which utilize the fossil fuel in a large extent which leads to air pollution and global warming. The massive utilization of Internal Combustion Engine (ICE) vehicles is contributed dramatically for the cause of depletion of fossil fuels and creates vigorous environmental pollution. These are the major attributes that makes us to think for an alternative source of energy mainly for the vehicle sectors. As a result an innovated concept of electric vehicle model is emerged in 1859 by Gaston Plante [2] using lead-acid battery. But frequent charging and discharging is carried out to propel the vehicle effectively that limit the total life of the battery. In order to meet the high power demand or vehicles having high power rating, a battery source is not sufficient to drive the vehicle because of its charge storage limitation. These arises the need for developing a prominent energy source for driving the electric vehicle. One such prominent energy source which attracts the researchers attention with its unique prominent feature is the fuel cell especially PEM (proton-exchange membrane) fuel cell. It is more preferable than the other types of fuel cells as it hold the features of high power density, solid electrolyte, low operating temperature (50˚C–100˚C), quick start-up, low sensitivity to orientation, favorable power to-weight ratio, long cell/stack life and low corrosion [3]. The existence of nonlinearity nature and the complex empirical relationship involved in the fuel cell increases the complexity of mathematical modeling and it also requires proper knowledge on processing parameters [4]. The complication arises with the mathematical modeling can be resolved using an artificial intelligent approach called neural network techniques. The main objective of this paper is focused on the design, modeling and simulation of neural network substituted PEM fuel cell operated electric vehicle operated with two different drive cycle (M-NEDC & M-UDDS).

The organization of the paper is as follows: Section II describes the development of Fuel Cell operated Electric Vehicle. Section III describes the Modelling of Static Feed Forward Network and Section IV describes the Modelling of cascaded Feed Forward Network. The Modelling of Fully Connected Recurrent Network and its results are presented in Sections V. The FCRN Network Operated Electric Vehicle Model and its simulation results for two different drive cycles are presented in Sections VI & VII. Finally, the conclusion is given in Section VIII.

II. Fuel Cell Operated Electric Vehicle

The modeling of PEM fuel cell powered electric vehicle incorporates the fuel cell energy source model, converter model and vehicle dynamics model. The operation inside the PEM fuel cell is highly nonlinear; hence there is a need to use the converter system (DC-DC) converter in order to deliver the stabilized output voltage to load. The designing of unidirectional DC-DC converter is based on their output current and voltage equation with the consideration of duty ratio of the converter. The electric vehicle designing also involves the vehicle dynamics modeling which encloses the motor model and the traction force acting on the vehicle, power at the wheel and produce torque and speed. The total resistive force acting on the wheel is the combination of forces such as grade force, rolling resistance force, aerodynamics drag force and inertial force. The vehicle dynamics modeling is develop with the concern of all these forces in action to drive the vehicle. One of the major aspects involved in the electric vehicle designing is the choice of drive cycle. Drive cycles that describes the standardized speed and road grade profile is used to estimate the performance of the vehicle. In this paper, two different drive cycle (M-NEDC & M-UDDS) are proposed for analyzing the several vehicle performance characteristics such as power availability, power requirement, distance covered by the vehicle using the two prescribed drive cycle along with the fuel consumption during the drive is also estimated. The mathematical modeling of fuel cell for developing an electric vehicle model is highly tedious, because the relationship between the PEM fuel cell's output voltage, stack temperature, partial pressure of hydrogen and oxygen inside the fuel cell are highly nonlinear and different kind of physical phenomena such as electrochemical and thermodynamic processes are involved in the model development [5]. Developing a precise model using the mathematical approach requires proper and accurate knowledge of processing parameter, which is difficult to estimate [6]. In order to eradicate the mathematical modeling complexity, an intelligent parametric modeling of PEM fuel cell using neural network approach is established that replaces the conventional mathematical modeling of PEM fuel cell. Among several neural network approaches, Feed-forward and Recurrent neural network structures are proposed to estimate the prediction performance of the 5KW PEM fuel cell. Based on the prediction capability, the reliable network can be chosen among the three networks for developing the neural network based fuel cell driven electric vehicle. In the preceding sections, the modeling of static & cascaded neural networks is discussed. Further, the development of electric vehicle model with the M-NEDC & M-UDDS drive cycle using the neural network substituted fuel cell is also discussed.

III. Modelling of Static Feed-Forward Network

A static feed forward neural (SFFN) network which implements the concept of error back propagation to the multiple layers in the neural network architecture that provide nonlinear mapping between input and output parameters. The SFFN network consists of three primary layers: input layer, hidden layer & output layer. The overall frame work for the proposed SFFN Network is shown in Fig.1. The three basic computation process visualized in the SFFN Network are: (i) Furnishing the Input Pattern (ii) Formulating Activation Net Values (iii) Evaluate the Network Performance.

The Network parameter selection is an important aspect in the modelling that includes the parameter and dimension specification includes the selection of training algorithm, activation function between input-hidden layer and hidden-output layer, feedback loop, epochs, number of input, hidden and output neurons and number of network layers. The parameters used for the designing of the SFFN are shown in Table I.

Table-I
Parameter Specifications

<table>
<tr><td colspan="2">Inputs</td><td>3</td></tr>
<tr><td colspan="2">Outputs</td><td>3</td></tr>
<tr><td colspan="2">Hidden layer</td><td>1</td></tr>
<tr><td colspan="2">Epochs</td><td>1000</td></tr>
<tr><td rowspan="2">Activation function</td><td>Input-Hidden</td><td>Tangential sigmoid</td></tr>
<tr><td>Hidden-Output</td><td>linear</td></tr>
<tr><td colspan="2">Error Goal</td><td>1E-06</td></tr>
<tr><td colspan="2">Training Algorithm</td><td>Levenberg-Marquardt back propagation</td></tr>
<tr><td colspan="2">Learning Algorithm</td><td>Gradient descent weight/bias</td></tr>
</table>

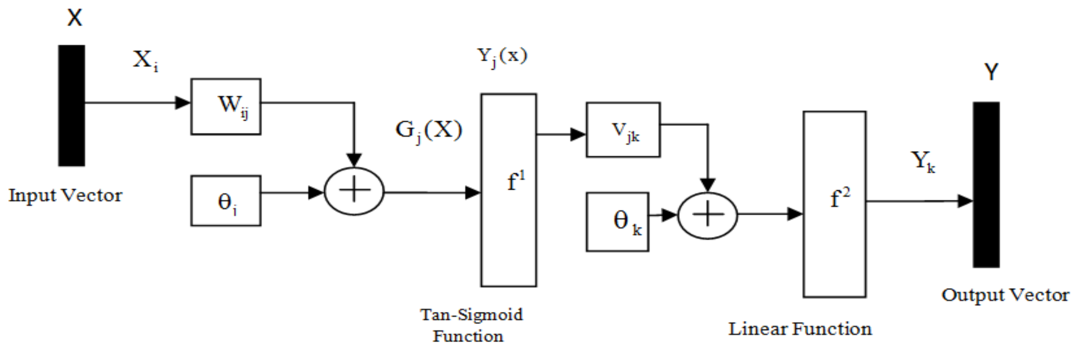

Fig. 1. Architecture of SFFN network model

Framework of SFFN Network

Step: 1 The network is initiated by providing input signal with weight function and bias to the input layer from the external environment is given as

$$G_j(X) = (\sum_{i=0}^{n} X_i \times W_{ij}) + \theta_j \tag{1}$$

Step: 2 The activation function is performed on the aggregated input signal propagated from the first layer. Since the input is ranged between [-1, 1], hence the hyperbolic tangential sigmoidal activation function is performed on the input signal is calculated as

$$Y_j(X) = \frac{e^{G_j(X)} - e^{-G_j(X)}}{e^{G_j(X)} + e^{-G_j(X)}} \tag{2}$$

Step: 3 The intermittent result from the hidden layer is propagated towards the next successive layer with appropriate weight links and bias. In order to provide linear output signal, the linear activation function is performed at the output layer is expressed as

$$Y_k = \left(\sum_{j=0}^{p} Y_j(X) \times V_{jk} \right) + \theta_k \tag{3}$$

The constructed network has to be trained with proper training. In this proposed work, Levenberg-Marquardt back propagation algorithm is used to train the network and after the training process, the prediction response from the proposed network model is compared with the actual target value for estimating the prediction ability and prediction error of the network. The network training performance in terms of Mean Squared Error (MSE value) and iteration value (EPOCHS) is shown in Fig. 2.

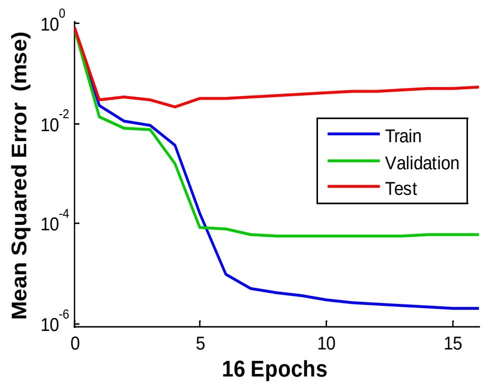

Fig. 2.Performance of SFFN Network

IV. MODELLING OF CASCADED FEED-FORWARD NETWORK

The Cascaded Feed Forward Neural (CFFN) Network is one of the feed forward network whose architecture is based on the error back propagated to the cascaded multi-layer neural network that provide nonlinear mapping between input and output parameters. This Cascaded Feed Forward Neural (CFFN) Network is designed for propagating the input vector to all the layers rather than providing input vector to the next preceding hidden layer from the input layer. This feature enhances the prediction performance of the proposed network. The network architecture for the Cascaded Feed Forward Neural (CFFN) network is shown in Fig. 3.

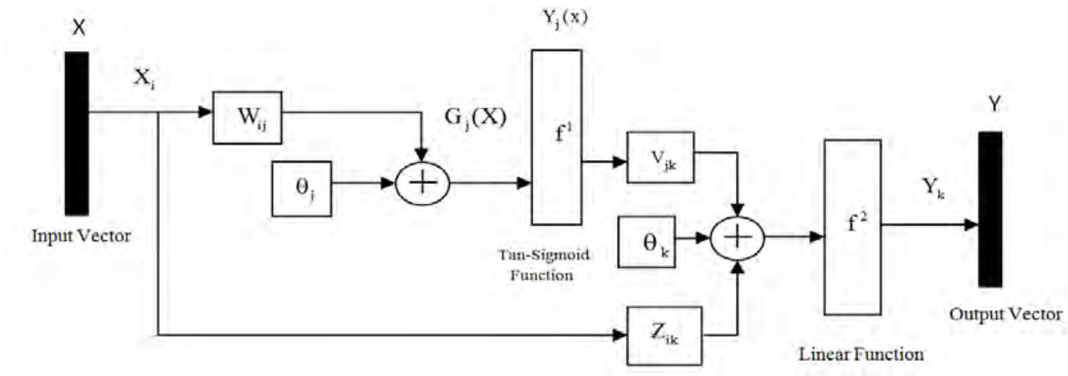

Fig. 3.Architecture of CFFN Network model

Framework of CFFN Network

Step: 1 The input vector in the input layer is summed up with the proper weight link and bias factor is propagated towards the entire layers in the network. The aggregated input signal is injected to the next layer such as hidden layer which is provided with 10 hidden layer neurons. In order to reduce the network complexity and to reduce huge weight link accumulation inside the network structure, the network structure with single hidden layer is used in this work. The network is initiated by providing input signal with weight function and bias to the input layer from the external environment is given as

$$G_j(X) = \left(\sum_{i=0}^{n} X_i \times W_{ij}\right) + \theta_j \tag{4}$$

Step: 2 The activation function is performed on the aggregated input signal propagated from the first layer. Since the input is ranged between [-1, 1], hence the hyperbolic tangential sigmoidal activation function is performed on the input signal is calculated as

$$Y_j(X) = \frac{e^{G_j(X)} - e^{-G_j(X)}}{e^{G_j(X)} + e^{-G_j(X)}} \tag{5}$$

Step: 3 The intermittent result from the hidden layer is propagated towards the next successive layer with appropriate weight links and bias. In order to provide linear output signal, the linear activation function is performed at the output layer is expressed as

$$Y_k = \left(\sum_{j=0}^{p} Y_j(X) \times V_{jk}\right) + \left(\sum_{i=0}^{n} X_i \times Z_{ik}\right) + \theta_k \tag{6}$$

After developing the network structure, it has to be trained with proper algorithm for mapping the input-output variable. After training, the prediction output response from the proposed network model is compared with the actual value for estimating the prediction ability and prediction error of the network. The network training performance in terms of Mean Squared Error (MSE value) and iteration value (EPOCHS) is shown in Fig. 4.

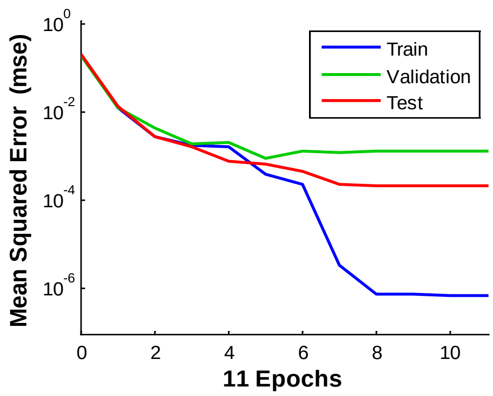

Fig. 4.Performance of CFFN Network

V. MODELLING OF FULLY CONNECTED RECURRENT NETWORK

The Fully Connected Recurrent Neural (FCRN) Network is one of the dynamic recurrent networks with fully connected recurrent loops that combine the unique features of both the partially recurrent neural networks. One of the partial recurrent networks that included in the Fully Connected Recurrent Neural (FCRN) Network is the ERN (Elman Recurrent Neural) network that provides the feedback recurrent connection from the output of the hidden layer to its input with some appropriate delay. The delay in this connection stores intermittent value from the previous time step, which can be used in the current time step prediction. An another partial recurrent network included in the FCRN Network is the NARX (Nonlinear Auto Regressive network with eXogenous Inputs) network that is based on the linear ARX model in which the next value of the dependent output signal is regressed on previous values of the output signal. The NARX network provides the recurrent feedback connection from the output to the input layer. The hybrid connection of FCRN Network provides the feedback loop from the hidden layer to the input layer with appropriate delay unit that stores the intermittent value from the hidden layer and another feedback loop connection from the output to the input layer with some delay that stores the past output in order to predict the output signal. In this proposed network, the present output value depends on both the past intermittent and past output value. The network architecture of Fully Connected Recurrent Neural (FCRN) Network is shown in Fig. 5.

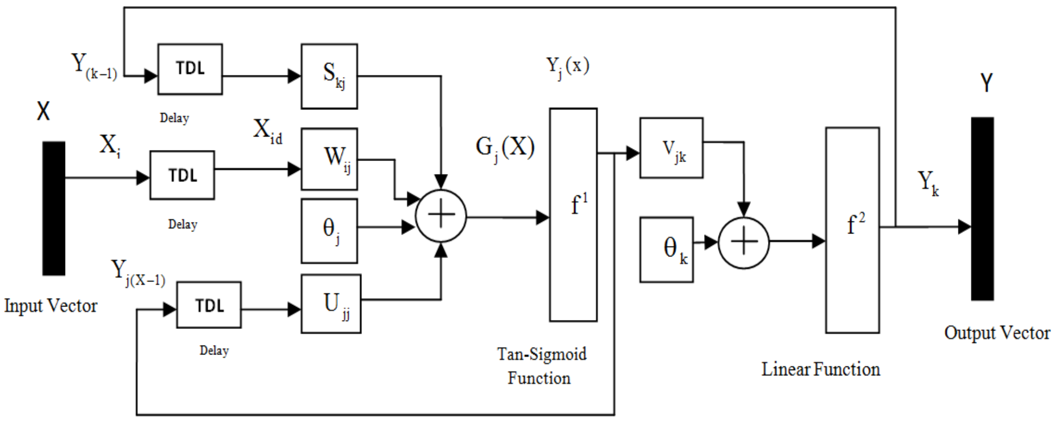

Fig. 5.Architecture of FCRN network model

Framework of FCRN Network

Step: 1 Neurons in the input layer acts as buffer for distributing the input signals to neurons in the hidden layer. Each neurons in the hidden layer sums up its input vector after weighting them with the strengths of the respective connections from the input layer and with the past intermittent value from the output of the hidden layer with corresponding weight links and appropriate delay unit and then finally sum up with the past output value with required weight connection and delay factor. The overall aggregated input signal from input layer is calculated as

$$G_j(X) = (\sum_{i=0}^{n} X_{id} \times W_{ij}) + (\sum_{j=0}^{m} Y_j(X-1) \times U_{jj}) + (\sum_{k=0}^{p} Y_{(k-1)} \times S_{kj}) + \theta_j \tag{7}$$

Step: 2 The tangential sigmoid activation function is performed on the aggregated input value to yield the actual output for each hidden node is estimated as

$$Y_j(x) = \frac{e^{G_j(X)} - e^{-G_j(X)}}{e^{G_j(X)} + e^{-G_j(X)}} \tag{8}$$

Step: 3 The output of neurons in the output layer is computed by performing linear activation function on the intermittent signal is estimated as

$$Y_k = \left(\sum_{j=0}^{m} Y_j(x) \times V_{jk} \right) + \theta_k \tag{9}$$

The developed network is trained with proper training algorithm for predicting the response of the system and after the training process, the prediction response from the proposed network model is compared with the actual target value for estimating the prediction ability and prediction error of the network. The network training performance in terms of Mean Squared Error (MSE value) and iteration value (EPOCHS) is shown in Fig. 6.

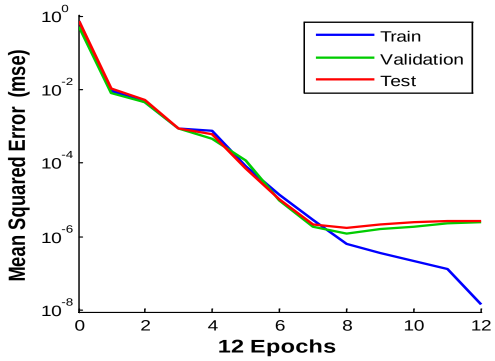

Fig. 6.Performance of FCRN Network

The comparative analysis is performed on the proposed Feed-Forward and Recurrent Neural Networks in terms of prediction performance error criteria such as: (i) MSE_t (Mean Square Error), (ii) $MAPE_t$ (Mean Absolute Percentage Error), (iii) MAE_t (Mean Absolute Error), (iv) R_t^2 (Coefficient of correlation) and (v) Iteration Value (EPOCHS) and are tabulated in Table – II. The formulation of the error criteria are given below:

i. Mean Square Error $MSE_t = \sum_{i=1}^{N_S} \frac{\left(P_i^{'} - P_i\right)^2}{N_S}$

ii. Mean Absolute Percentage Error $MAPE_t = \frac{100}{N_S} \sum_{i=1}^{N_S} \left| \frac{\left(P_i^{'} - P_i\right)}{\overline{P_i}} \right|$

iii. Mean Absolute Error $MAE_t = \frac{1}{N_S} \sum_{i=1}^{N_S} (P_i^{'} - P_i)$

iv. Coefficient of correlation $R_t^2 = 1 - \frac{SSE_t}{SST_t}$

Where, P_i is predicted output, $P_i^{'}$ is actual output; $\overline{P_i}$ is average actual output and N_S is number of samples; SSE_t = Sum of squares due to error & SST_t= Total sum of squares

TABLE II NUMERICAL ANALYSIS OF NEURAL NETWORKS

Neural Networks	SFFN	CFFN	FCRN
MSE_t	1.979E-06	7.031E-07	1.1876E-08
$MAPE_t$	0.0160	0.0042	8.871E-04
MAE_t	0.0075	9.6238E-04	1.1124E-05
R_t^2	0.8157	0.99	1.000
EPOCHS	16	11	12

From the performance analysis, it can be evident that the Fully Connected Recurrent Network (FCRN) yield better prediction performance with the minimum error value of 1.1876E-08 in 12 epochs. The FCRN network met error goal with fast convergence rate and minimum error value than other two Feed Forward Networks. The dynamic behavior of stack output voltage for the proposed cascaded network based 5kW Ballard PEMFC system is shown in Fig. 7 for the load current change over a short period of time from 0 to 8 seconds between 90A and 40A. The simulation results obtained from the proposed cascaded network model is used to analyze the dynamic behavior of the 5kW PEM Fuel cell system. The dynamic response from the developed network model is validated with the experimental result obtained from the Ballard-Mark-V PEM Fuel cell model [8].

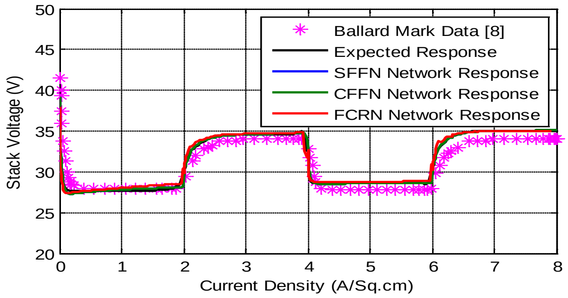

Fig. 7.Dynamic Stack Voltage Response

VI. FCRN NETWORK OPERATED ELECTRIC VEHICLE MODEL

The development of the neural network substituted fuel cell based electric vehicle model incorporates the modeling of optimum neural network structure, DC-DC converter system and vehicle dynamics modeling with two different drive cycle. The simulation work of the proposed electric vehicle model is carried out using MATLAB / simulink to verify the reliability of the vehicle performance for the different drive cycle (M-NEDC and M-UDDS) used and the output performance such as power availability, power requirement for the propulsion of vehicle, distance covered and fuel consumption for the different drive cycles (M-NEDC and M-UDDS) are analyzed. From the previous section, it can be concluded that the Fully Connected Recurrent Network (FCRN) yield better prediction performance with the minimum error value and provide fast convergence rate than the Feed Forward Networks. Hence the Fully Connected Recurrent Network (FCRN) is chosen as an optimal network for developing an electric vehicle. But the output voltage response from the proposed neural network based fuel cell system is highly dynamic in nature. There arises a need for converting the unregulated DC output voltage to the DC regulated voltage by means of power electronic circuitry of DC-DC converter to provide a constant output voltage to vehicle dynamics/transmission control module. The input voltage to the converter module is the unregulated output voltage from the fuel cell stack. The duty cycle in this DC-DC converter is obtained by integrating the difference voltage obtained by subtracting the reference voltage from the output voltage response of the preceding fuel cell stack module. The proposed converter should be of unidirectional one, since the fuel cell cannot have the ability to utilize the power developed during regenerative braking.

The next process involved in the development of electric vehicle model is the development of vehicle dynamics/Transmission Control Module. The vehicle dynamics modeling is designed in concern with the total resistive force acting on the vehicle and power required to propel the vehicle [11].The total resistive force acting on the wheel is the combination of forces such as grade force, rolling resistance force, aerodynamics drag force and inertial force. The vehicle dynamics modeling is developed with the concern of all these forces in action to drive the vehicle and the developed simulink model for the proposed electric vehicle model is represented in Fig.8. The vehicle parameters specifications are taken from [12].

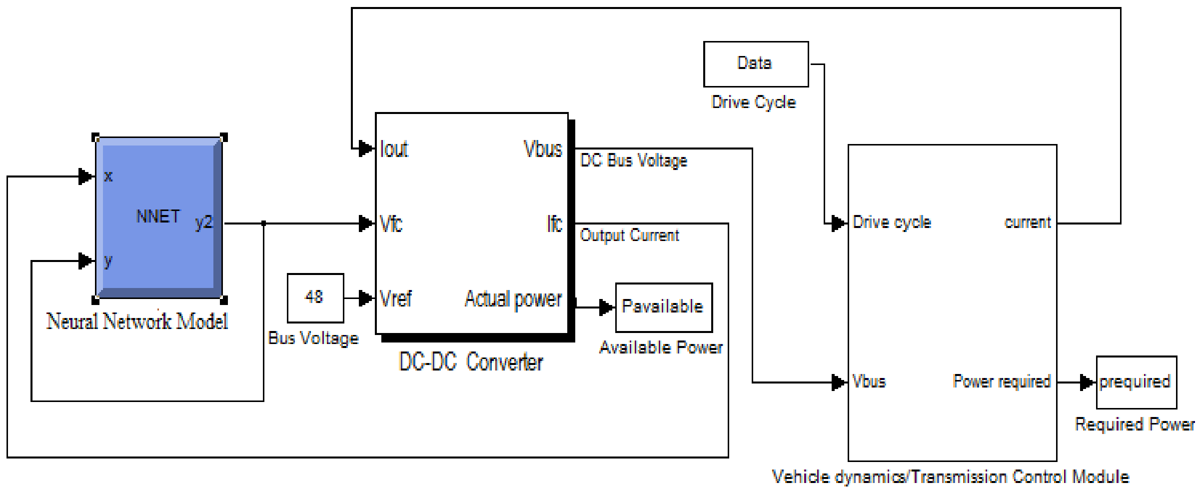

Fig. 8.Simulink Model of Proposed Electric Vehicle System

VII. SIMULATION RESULT

The simulation work is carried out to predict the performance of Fully Connected Recurrent Neural (FCRN) Network based fuel cell operated electric vehicle that involves power availability, power requirement, distance covered by the vehicle for the two different drive cycle (M-NEDC and M-UDDS) and fuel consumed to drive the vehicle is also estimated.

A. Simulation result of electric vehicle using M-NEDC Drive Cycle

The Modified New European Driving Cycle (M-NEDC) simulates during 1200 seconds is used to simulate the urban and sub urban route with frequent stops but insufficient in frequent starting operation. The Modified New European Driving Cycle (M-NEDC) is provided with the maximum range of 60km/hr is used to verify the capability of the proposed electric vehicle model and it is shown in Fig. 9. With this driving cycle the power requested to the drive the electric vehicle and the power available from the proposed energy source (neural network based fuel cell) is shown in Fig. 10. The NEDC drive cycle runs a distance of around 5500 meters in 1200seconds and it is depicted in Fig. 11 and the amount of hydrogen fuel consumption in kilogram per second is shown in Fig. 12.

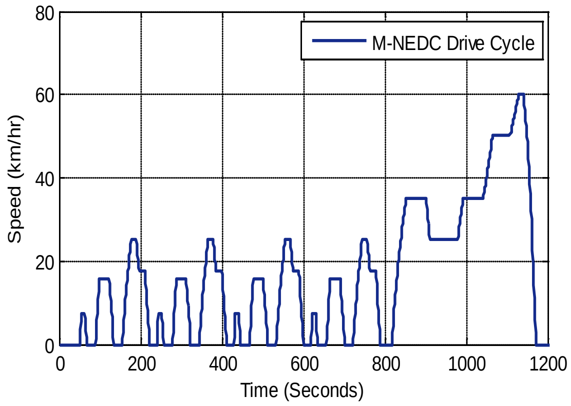

Fig 9.M-NEDC Drive cycle pattern

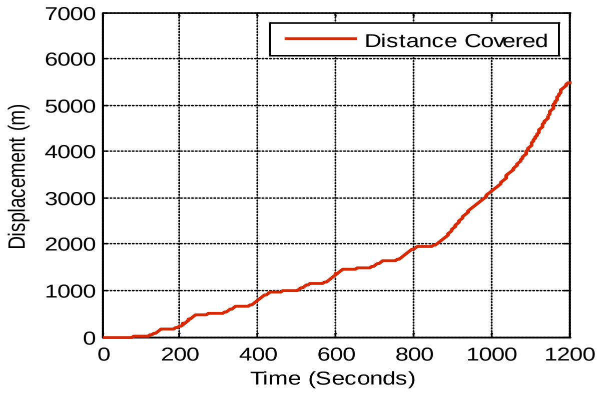

Fig. 11.Distance coverage with the M- NEDC Drive cycle

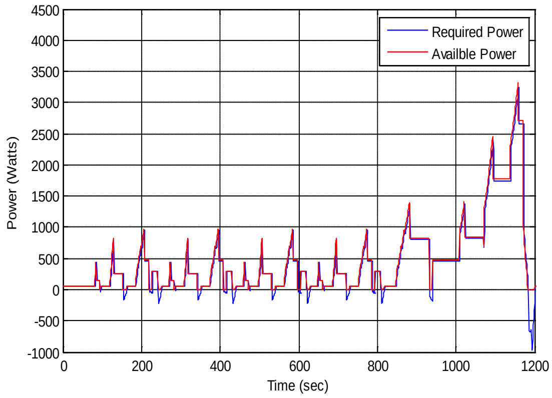

Fig. 10.Comparison analysis of power with M-NEDC Drive cycle Pattern

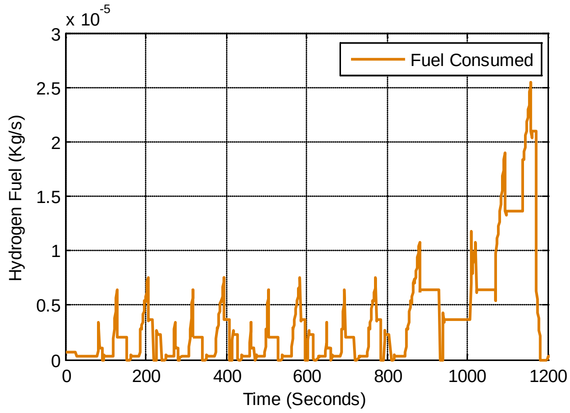

Fig. 12.Fuel consumed for the M-NEDC Drive cycle Pattern

B. Simulation result of electric vehicle using M-UDDS Drive Cycle

The Modified Urban Dynamometer Driving Schedule (M-UDDS) drive cycle is used to simulate the urban/city driving of a vehicle that providing frequent start and stops. The frequent start and stop characteristics of the city driving is more suitable to recapture energy using regenerative braking. Fig. 13 shows the Modified Urban Dynamometer Driving Schedule cycle (M-UDDS) with the maximum range of 45km/hr is used to verify the optimality of the electric vehicle model. The comparative analysis graph for power available to drive the vehicle and power required for the M-UDDS drive cycle is shown in Fig. 14. The M-UDDS drive cycle runs a distance of around 6000 meters in 1369 seconds and it is depicted in Fig.15 and the amount of hydrogen fuel consumption in kilogram per second is shown in Fig. 16.

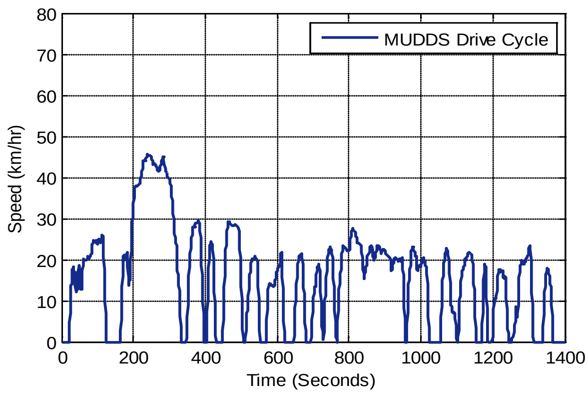

Fig. 13.M-UDDS Drive cycle pattern

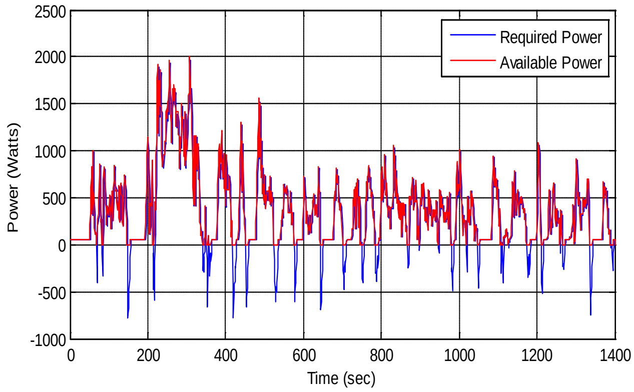

Fig. 14.Comparison analysis of power with M-UDDS Drive cycle Pattern

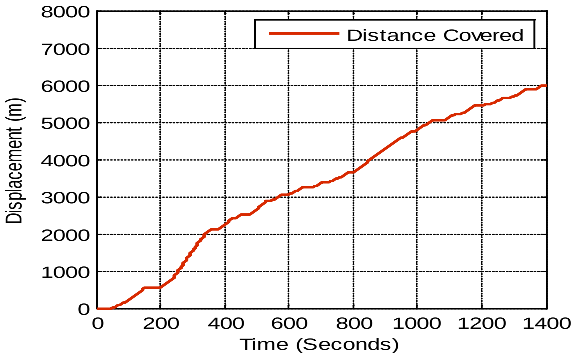

Fig. 15.Distance coverage with the M-UDDS Drive cycle Pattern

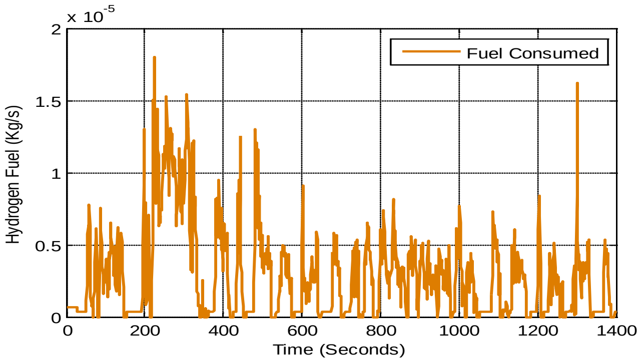

Fig. 16.Fuel consumed for the M- UDDS Drive cycle Pattern

VIII. CONCLUSION

The study carried out in this paper for modelling the Proton Exchange Membrane Fuel Cell system is done using Feed Forward & Recurrent Neural Networks are more appropriate in Automotive Applications. The results obtained from the proposed Neural Network Architectures clearly reveals that the prediction ability of the Fully Connected Recurrent Network (FCRN) is comparatively appreciable than other two Feed Forward Neural Network in terms of various error criteria such as Mean Square Error, Mean Absolute Percentage Error, Mean Absolute Error, Coefficient of correlation and Iteration Values. Henceforth, the Fully Connected Recurrent Network (FCRN) is preferred as an optimal network to be used with the proposed fuel cell powered electric vehicle system. In view of this, a model of optimal neural network based fuel cell operated electric vehicle is designed and a simulation study of the proposed vehicle is performed in this paper to test the optimality of the model proposed. Investigation of the vehicle performance is done based on the distance coverage, hydrogen fuel consumption and power flow within the vehicle whose behaviour is mainly influenced by the use of drive cycle pattern. Two popular modified drive cycles (M-NEDC and M-UDDS) are considered in this simulation study of the developed vehicle and a comparative analysis is accomplished for its performance exploration. From the simulation results, it is clearly evident that the proposed model can provide a complete solution for the fuel cell vehicle related studies which eradicate the need of fossil fuels for its powering. Further, the cold start issues intricate with the stand alone fuel cell operated vehicle can get rid of by developing a hybrid electric vehicle model with the inclusion of batteries or ultra-capacitors etc. as a backup power source.

REFERENCES

[1] BP Statistical Review of World Energy, June 2007, www.bp.com/statisticalreview.
[2] J. Terras, A. Neves, D. Sousa and A. Roque, “Modeling and Simulation of a Commercial Electric Vehicle,” 13th International IEEE Annual Conference on Intelligent Transportation Systems, September 2010.
[3] J. T. Pukrushpan , A. G. Stefanopoulou, and H. Peng, “Control of fuel cell breathing,” IEEE Control Syst. Mag., vol. 24, no. 2, pp. 30–46, Apr.2004 .
[4] Pasricha.S and Shaw.S.R, “A dynamic PEM fuel cell model,” IEEE Trans. Energy Convers. , vol. 21, no. 2, pp. 484–490, Jun. 2006.
[5] C. Wang, M. H. Nehrir, and S. R. Shaw, “Dynamic models and model validation for PEM fuel cells using electrical circuits,” IEEE Transactions on Energy Convers., vol. 20, no. 2, pp. 442–451, Jun. 2005.
[6] W. Friede, S. Rael, and B. Davat, “Mathematical model and characterization of the transient behavior of a PEM fuel cell,” IEEE Trans. Power Electron., vol. 19, no. 5, pp. 1234–1241, Sep. 2004.
[7] H.B. Demuth, M. Beale, Users’ Guide for the Neural Network Toolbox for Matlab, The Mathworks, Natica, MA, 1998.
[8] Chien-Hsing Lee et al., “Modeling of the Ballard-Mark-V proton exchange membrane fuel cell with power converters for applications in autonomous underwater vehicles”, J. Power Sources., 196 (2011) 3810-3823.
[9] Tsungnan Lin, Bill G. Horne, Peter Tino, C. Lee Giles, Learning long-term dependencies in NARX recurrent neural networks, IEEE Transactions on Neural Networks, Vol. 7, No. 6,1996, pp. 1329-1351.
[10] L. Marquez, T. Hill, R. Worthley, W. Remus, “Neural network models as an alternative to regression”, Proceedings of the 24th Annual Hawaii International Conference on System Sciences, IEE Comput. Soc. Press, Kauai, Hawaii, Vol. 4 pp.129-35.1991.
[11] M. Xianmin, “Propulsion system control and simulation of electric vehicle in MATLAB software environment”, Proceeding of the 4th World Congress on Intelligent Control and Automation 2002, pp. 815-818, June 2002.
[12] Bruce Lin,” Conceptual design and modeling of a fuel cell scooter for urban Asia”,Elsevier Journal of Power Sources, vol. 86, pp. 202-213, 2000.