Comparative Study of Recurrent and Non Recurrent Neural Network Based Approach for Modeling of PEM Fuel Cell Powered Electric Vehicle

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Abstract. In this paper, a non recurrent Focused Time Delay Neural Network (FTDN) and a recurrent nonlinear autoregressive network with exogenous inputs (NARX) Neural Network are employed as a black box prediction model for substituting the complex conventional model of PEM 5kW Proton Exchange Membrane (PEM) Fuel Cell system. A comparative assessment is performed between the recurrent and non recurrent neural network on certain performance measures to identify an optimal network for modeling the PEM Fuel Cell System in PEM Fuel Cell powered electric vehicle application. From the simulation result, it is observed that the recurrent NARX network is showed excellent prediction ability in terms of minimizing the Mean Square Error (MSE) value with faster convergence. The optimized network is tested with intermittent data for examining its adaptability and validated with experimental benchmark data for proving its reliability. Hence the optimum network is integrated with converters and vehicle dynamic system to develop a fuel cell based electric vehicle system. The performance of the proposed vehicle is tested with US06 drive cycle pattern for justifying its reliability.

1. Introduction

Hydrogen related studies especially generation from renewable sources and utilization with improved fuel economy has grasped great attention of researchers worldwide in the recent years [1]. As a clean energy source, PEM Fuel cell with its high efficiency, modularity, flexibility and fast load response are well applicable factors to be employed in vehicular and house hold applications [2]. Meanwhile, it is a huge challenging task to represent a transient behavioral system using empirical or semi empirical model with fixed parameters because the system is subjected to temporal variation due to non observable and non predictable changes on internal conditions uncertainly [3] and [4]. Estimating or approximating the system parameters is not been well appropriate for all the conditions especially for the long term précised prediction. These modelling constraints is effectively resolved using a powerful data mapping and modeling tool termed as ‘neural network modeling’ or it is also termed as ‘black-box models’ which provide better approximation without characterizing the complex input and output relationships [5].

Some of the related studies that spotlighted on the modeling of neural network controller using either non recurrent neural network or dynamic recurrent network or both are elucidated as follows.
Puranik et al. implemented a modified version of NARMAX recurrent neural network model for a 500-W PEMFC stack for examining the long and short term transient dynamics [6]. The training data is extracted from the nonlinear State-Space simulation model of PEMFC system [7]. Yu et al. has [8] determined the optimal linear operating point of fuel cell for obtaining a maximum and stable power density with the combined effect of Taguchi approach and neural networks against different current densities. The proposed neural network is trained for establishing the relationship between various control factors . Hayder et al. has optimized the fuel cell performance for different pressure and load by the influence of PID Controller whose gain is tuned with PSO technique [9]. Load tracking ability of neural network equipped with Fuzzy Logic Controller is examined by Mammar et al. [10] and it is mainly for residential application and subjected to abrupt load changes of active and reactive power demand thereby the flow of hydrogen for the load change can be effectively controlled.

This paper is focused on précised prediction of a time varying, uncertain and multivariable PEM Fuel Cell system using system identification approach as a substitution of complex conventional modeling in electric vehicular applications. For which, a tapped time delayed non recurrent network FTDN and recurrent network NARX are developed and compared with certain performance measures such as Mean Square Error (MSE), epochs and correlation (R).

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![Figure 1. NN based PEM fuel cell powered electric vehicle system.](image_url)

The optimum network is incorporated with DC – DC converter and transmission system to form a complete vehicle traction system. The overall layout of the neural network based PEM fuel cell powered electric vehicle system is presented in figure 1.

2. **Modeling of ANN based PEM fuel cell powered electric vehicle system**

The major aspects involved in the modeling of the ANN based PEM fuel cell powered electric vehicle system are the modeling of energy sources, the power electronic circuitry and the transmission systems. The main use of source in the vehicle traction system is to provide the supply for the load demand. The fuel cell energy source preferred here is the Proton Exchange Membrane (PEM) Fuel Cell because of its low operating temperatures, sustained operation at a high current density, low weight, compactness, the potential for low cost and volume, longer stack life, fast start-ups and suitability for discontinuous operation is prioritized among other types [2].

The Artificial Neural Network (ANN) is substituted as a black box for predicting the PEM Fuel Cell response that provide appropriate mapping between the input and the output of the PEM fuel cell without acquiring any empirical relationship inside the PEM Fuel cell [11]. The fluctuated output response from the source is regulated with the power electronics DC-DC converter unit. Since the fuel cell is only provided the supply to the load demand and lack of utilizing the regenerative power during braking process a unidirectional DC-DC converter unit is used.

The Dynamic behavior of the electric vehicle is modeled with the consideration of all the forces applied to the vehicle. The net force acting at the wheel of the vehicle for its propulsion is the combination of two forces that are tractive and resistive force. The tractive force applied along the direction of the movement of the vehicle while the resistive force applied in the opposite direction of the movement of the vehicle.
The four major components acting against the vehicle are the combination of aerodynamics force, rolling resistance force, inertial force and gradient force [12]. A simplified equivalent model of the vehicle dynamics can be used to estimate the tractive requirement of the vehicle drive-train that comprising of all the relative forces is showed in figure 2. The vehicle specification to be used for the modeling of the proposed electric vehicle model is taken from the literature [13].

**Figure 2.** Simplified view of vehicle dynamics model.

### 3. Non Recurrent and Recurrent Neural Network

The Artificial Neural Network (ANN) is not required the knowledge of various empirical set of equation inside the fuel cell system or any processing parameter assumptions to reduce the overall complexity of the model. This approach not only reducing the complexity involved in the mathematical modeling but also reducing the time required to develop the model. The general block diagram representation of neural network approach for the prediction of output response is shown in figure 3.

**Figure 3.** ANN modeling approach.

The polarization dynamics of PEM Fuel Cell is described the input output parameter for the NN modeling of PEM Fuel Cell. The effect of current density, hydrogen partial pressure and oxygen partial pressure on cell voltage and stack power prediction is investigated by keeping Stack temperature at 72 degree and Membrane Water Content at 14 as constant values. The data required to training the network is extracted from the Ballard-Mark-V 35-cell 5 kW PEM Fuel Cell experimental result from literature [14] and its specification is given in table 1. Among which 60% data set is used for training and remaining 40% data set is used for testing and validation. The raw extracted data are
differed in their units and numerical data range and it is pre-processed to obtain a normalized data within a specific range -1 to 1 or 0 to 1 for improving the accuracy of subsequent numeric computation. In this paper, the raw data are normalized within -1 to 1 value and it is again denormalized to its original unit and range. The parameters used for modeling the dynamic non recurrent and recurrent neural networks are shown in table 2.

Table 1. Specifications of Ballard-Mark-V PEMFC system [15].

| Component                      | Value          |
|--------------------------------|----------------|
| Stack temperature             | 72             |
| Active area of the cell       | 232 cm²        |
| Anode pressure                | 3 atm          |
| Cathode pressure              | 3 atm          |
| Number of cells in the stack  | 35             |
| Anode volume                  | 0.005 m³       |
| Cathode volume                | 0.01 m³        |
| Membrane dry density          | 0.002 kg/cm³   |
| Membrane dry Eq. weight       | 1.1 kg/mol     |
| Membrane thickness            | 0.0178 cm      |

Table 2. Network parameter selections.

| Inputs: Outputs | 3:2 |
|----------------|-----|
| Hidden layer   | 1   |
| Hidden layer Neurons | 20 |
| Delay          | 1:2 |
| Epochs         | 1000|
| Activation function | Hidden Tangential sigmoid |
|                | Output Linear |
| Training Algorithm | Levenberg-Marquardt [19] |

3.1. FTDN Network
A non recurrent Focused Time Delay Neural Network (FTDN) is also a dynamic network whose dynamic exist as a time delay variant only at a input layer and remaining parts resembles a static multilayer feed forward network. The FTDN Network is suitable for time series prediction and provided one step-ahead prediction. The tapped delay lines at input layer is enhanced the prediction ability than a static feed forward network by reducing the conflicts of propagating the input vector to the input nodes and the network provide faster training than other conventional dynamic networks because the tapped delay lines appears only at the input layer and the network does not contain any feedback loops or any adjustable parameter in between the network layers. Hence it does not require dynamic back propagation to compute the network gradient. This makes the convergence at the faster rate than other dynamic networks. The mathematical model of FTDN Network is showed in figure 4 and their representations are given in equation (1), (2), (3) and (4).
Figure 4. Mathematical model of FTDN network.

The input vector \((X_i)\) after tapped delay \((X_{id})\) with its corresponding synaptic weight links \((W_{ij})\) and bias factor \((\theta_i)\) are furnished as a net input value \((G_j(X))\) and disseminated from the input layer towards the hidden layer is given in equation (1). The propagated input \((G_j(X))\) is functioned with tangential sigmoid activation function at the hidden layer is given in equation (2). Then the intermittent response \((Y_j(x))\) with corresponding synaptic weight links \((V_{jk})\) and bias factor \((\theta_k)\) are aggregated as \(Y_k(X)\) and propagated towards the output layer for linear activation to yield a network output response \((Y_k)\) are given in equation (3) and (4).

\[
G_j(X) = \left( \sum_{i=1}^{n} X_{id} \times W_{ij} \right) + \theta_j
\]  
(1)

\[
Y_j(x) = f^1(G_j(X))
\]  
(2)

\[
Y_k(X) = \left( \sum_{j=0}^{N} Y_j(x) \times V_{jk} \right) + \theta_k
\]  
(3)

\[
Y_k = f^2(Y_k(X))
\]  
(4)

3.2. NARX Network

The dynamic recurrent nonlinear autoregressive network with exogenous inputs (NARX) is constructed with feedback connection from output to the input layers of the network. In this network, the output signal from the network is regressed on past values of the output signal and present values of an independent (exogenous) input signal [16] and [17]. The dynamic recurrent NARX neural network mathematical model is showed in figure 5. The network is triggered by providing the input vector to the n input nodes in the network input layer that disseminated towards the successive layer with appropriate delays, weight links and bias between the layers.

Figure 5. Mathematical model of NARX network.

The mathematical representation of these computations is represented in equation (5), (6), (7) and (8). The input vector \((X_i)\) after tapped delay \((X_{id})\) with its corresponding synaptic weight links \((W_{ij})\), past recurrent output vector \((Y_{ik-1})\) after tapped delay \((Y_{dik-1})\) from output layer with corresponding
synaptic weight links \((S_{kj})\) and bias factor \((\theta_j)\) are aggregated as a net input value \((N_j(X))\) that propagated towards the hidden layer is given in equation (5). These values are functioned with tangential sigmoid activation function at the hidden layer is given in equation (6). Then the intermittent response \((Y_j(x))\) with corresponding synaptic weight links \((V_{jk})\) and bias factor \((\theta_k)\) are aggregated as \(Y_k(X)\) and propagated towards the output layer for linear activation to yield a network output response \((Y_k)\) are given in equation (7) and (8).

\[
N_j(X) = \sum_{i=0}^{p_n} X_{ni} \times W_{ij} + \sum_{k=0}^{p} Y_{(k-1)j} \times S_{kj} + \theta_j
\]

(5)

\[
Y_j(x) = f^1(N_j(X))
\]

(6)

\[
Y_k(X) = \left( \sum_{j=0}^{q} Y_j(x) \times V_{jk} \right) + \theta_k
\]

(7)

\[
Y_k = f^2(Y_k(X))
\]

(8)

4. Simulation Result of Neural Network Modeling

The prediction of the proposed non recurrent and recurrent in terms of Mean Square Error (MSE), epochs and correlation (R) are investigated and compared for the optimum network identification that can be substituted as a PEM Fuel Cell black box model. The prediction performance of the FTDN Network for the training, validation and testing data set in terms of Mean Square Error (MSE) is showed in figure 6.

![Figure 6. Prediction response of FTDN network.](image)

![Figure 7. Steady state response of FTDN network.](image)
The best validation performance is $6.0527 \times 10^{-5}$ attained at 14 epochs. The steady state V-I characteristics of NN based PEM Fuel Cell is validated with the experimental data from literature [18] and it is depicted in figure 7.

The prediction performance of the NARX Network for the training, validation and testing data set in terms of Mean Square Error (MSE) is showed in figure 8. The best validation performance is $8.4675 \times 10^{-7}$ attained at 11 epochs. The recurrent NARX network is showed far excellent result with minimum prediction error at a fast convergence rate than non recurrent FTDN network. The fitness of optimum NARX network prediction response with real experimental response in terms of Correlation factor values ($R$) for the training and validation data are showed in figure 9. The predicted response is showed good congruence with real measured value with $R=0.99999$ for the training data set and $R=0.99957$ for the validation data set.

![Figure 8. Prediction Response of NARX Network.](image)

![Figure 9. Correlation factor values of NARX Network.](image)

The behavioral analysis of the optimum NARX network is carried out and validated the response with the experimental plant response from the literature [18]. In the steady state response analysis, cell voltage against current density and stack power against current density curves are investigated and depicted in figure 10 and 11. While in the transient response analysis, dynamic time varying stack voltage response and stack power response with respect to time are analyzed and depicted in figure 12 and 13.
Figure 10. Polarization curve of NARX network.

Figure 11. Stack power estimation curve of NARX network.

Figure 12. Stack voltage estimation curve of NARX network.
Both steady state and dynamic response of proposed ANN based PEM Fuel Cell extremely congruence with the experimental plant response. Hence the dynamic recurrent NARX network is declared as an optimum network to be used for further development in NN Based PEM Fuel Cell Electric Vehicle Model.

5. Results and Discussion

The MATLAB/Simulink platform is used to develop the ANN Based PEM Fuel Cell Electric Vehicle Model in which the optimum NARX network is integrated with DC – DC converter and vehicle dynamics and its Simulink Model is showed in figure 14. An unregulated DC output voltage form ANN based PEM Fuel Cell is regulated by means of power electronic circuitry of DC-DC converter and it propagated toward the vehicle transmission system for delivering the requested power at the wheel of the vehicle. Since PEM Fuel cell is a unidirectional energy source and lack of utilizing regenerative braking power, a unidirectional DC-DC converter is used in this paper.

A standardized driving pattern that described by means of a speed time table is used as reference drive cycle to analyze and compare the proposed vehicle performances. Among several driving patterns, US06 drive cycle with the maximum range of 35km/hr is used in this paper for analyzing the performance of the proposed vehicle and is showed in figure 15. The vehicle runs a distance of around 26 km/hr in 1200seconds for US06 drive cycle is shown in figure 16.
The power required at the wheel of the vehicle for the US06 drive cycle is compared with power delivered from the NN Based PEM Fuel Cell is showed in Figure 17. It is observed that, the proposed vehicle model is delivered the acceleration power demanded at the wheel of the vehicle but it is lacked in utilizing the negative regenerative braking power in an effective manner.

Figure 17. Comparison of requested power for US06 drive cycle with available NN based PEM fuel cell power.
6. Conclusion
Two dynamic networks such as a non recurrent Focused Time Delay Neural Network (FTDN) and a recurrent NARX Neural Network are developed and compared for identifying an optimum network to be employed for establishing a box NN based PEM Fuel Cell model. It is observed from the simulation result that the NARX Neural Network is showed improved prediction performance with minimum Mean Square Error (MSE) value of 8.4675e-07 at 11 epochs for the validation data than the FTDN network. The static and dynamic behavior analyses of optimum are carried out and validated the networks response with experimental benchmark data. ANN based PEM Fuel Cell powered electric vehicle model is developed by incorporating the optimum NARX Neural Network as a energy source with the unidirectional DC-DC converter units and vehicle dynamic system. The performance of the proposed vehicle model is investigated with US06 drive cycle pattern in terms of power requirement, power availability from the energy source and distance coverage. It is observed that, the proposed vehicle model has delivered the acceleration power but it is lacked in utilizing the negative regenerative braking power in an effective manner. In future, it is planned to develop a hybrid electric vehicle model for utilizing the braking power and to extend the life of energy source with improved drivability.

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