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Neural network based control for PEM fuel cells

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ABSTRACT : *The main objective of this paper is to overcome the transient variations in the dynamic loads of PEM fuel cells. These variations will affect the overall performance of the fuel cell. So a control strategy based on neural network is proposed in this paper. This neural network predictive system behavior is investigated under random current variations. The proposed neural network model is a fast and proper control system for controlling the fuel cell terminal voltage and improving the system performance.*
Keywords – *Reversible voltage, Irreversible losses, flow rate, predictive control.*

1. Introduction

A Fuel cell is an electrochemical device which converts chemical energy directly into electrical energy by combining hydrogen fuel with oxygen. Based on the type of electrolyte, Fuel cells can be classified into Alkaline Fuel Cells (AFC), Phosphoric Acid Fuel Cells (PAFC),Solid Oxide Fuel Cells(SOFC),Molten Carbonate Fuel Cells(MCFC) and Proton Exchange Membrane Fuel Cells(PEMFC)[1].Most of the practical applications uses PEMFC type of fuel cell because of its main characteristics like high power density, greater efficiency, long cell and stack life. Fig.1 shows the schematic diagram of a PEMFC. The working of PEMFC is as follows: The hydrogen fuel which enters the anode passes through the diffusion layer to reach the catalyst where it gets splitted into protons and electrons. The protons are then allowed by the proton exchange membrane to reach the cathode and the electrons are allowed to flow through an external load .At the cathode, Oxygen combines with protons and electrons to form water. These thermo dynamical reactions like diffusion, ionization are closely associated with the factors like humidity, temperature, air flow rate, hydrogen flow rate and pressure..Since the fuel cell voltage is varied under various parameters this will affect the performance in practical applications. Therefore a control strategy should be developed to predict the control signals and to keep the terminal voltage constant[2].

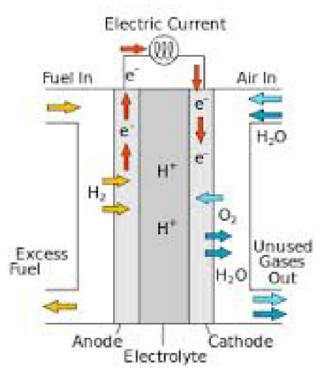

Fig.1.Schematic Diagram of PEMFC Mechanism

This paper is organized as follows: In section II, Proton Exchange Membrane Fuel cell Model is discussed. In section III a brief description about neural network controller is given. The simulation results are discussed in section IV. Finally, the paper is concluded in Section V.

2.Proton Exchange Membrane Fuel cell Model

The output voltage of a cell is defined according to Nernst Equation by the following expression

$$V_{cell}=E-V_{act}-V_{ohm}-V_{con} \tag{1}$$

Where E is the reversible cell voltage .V_{act} ,V_{ohm} and V_{con} are activation, ohmic and concentration voltage drops respectively.

The actual potential of a fuel cell is 1.3V.But it is decreased from its equilibrium value because of the irreversible losses created by activation polarization, ohmic polarization and concentration polarization[3].

Consider a fuel cell stack formed by connecting n cells in series with the stack voltage given by

$$V_{stack} = nV_{cell} \tag{2}$$

2.1.Reversible Cell Voltage

The reversible voltage of PEM fuel cell is given by

$$E= n_S E_O^{cell} + \frac{n_S RT}{2F} \ln\frac{[P_{H2}(P_{O2})^{0.5}]}{P_{H2O}} \tag{3}$$

Where E_O^{cell} is the open circuit votage

R is gas constant(8.3144J/mol.K)

T is the operating temperature

P_{H2},P_{O2}, P_{H2O} are the partial pressures of each gas inside the cell

F is the Farady's Constant(101 325Pa)

2.2.Irreversible Voltage Losses

Three types of voltage losses like activation losses, Ohmic losses and Concentation losses exist within PEM Fuel Cell.

1.Activation Losses: Due to the slow operation of electrode at the electrode surface gives this type of loss in PEM Fuel cell. They are dominant at low current density and the loss is given by

$$V_{act} = \frac{RT}{2F}\ln(I/I_d) =a_0 + T[a+b \ln(I)] \tag{4}$$

Where the term (a_o +aT) represents temperature dependent voltage loss and the term [Tb ln(I)] represents activation loss based on both current and temperature.

2.Ohmic Losses: This is due to the ohmic resistance of the PEM fuel cell that includes the resistance of the cathode and the anode due to manufacturing imperfections

The ohmic voltage loss for a single PEM fuel cell stack can be given as follows

$$V_{ohm}= IR^0= V_A^{\,0}+ V_C^{\,0} + V_M^{\,0} \tag{5}$$

3.Concentration losses: This type of loss is due to the concentration variation of the reactants at the surface of the electrodes. It is given by

$$V\ conc= -\frac{RT}{eF} \ln(1-I/I_L) \tag{6}$$

In PEM fuel cell positive hydrogen ions reach the cathode through the membrane and electrons reach the cathode through the external circuit forming charged layer at the cathode. This charge double layer can store electrical charge and behaves like a capacitor. This double layer plays an important role in the dynamic response of the PEM fuel cell[3].

The fuel cell polarization curves is shown in fig.2

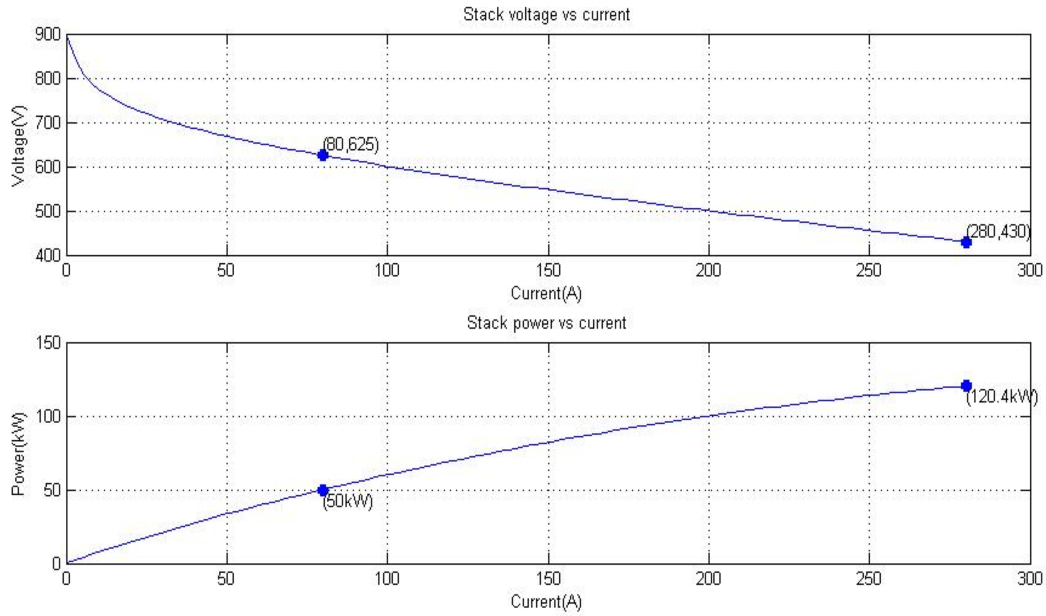

Fig.2.Polarization Curves

3.Neural Network controller

The neural network predictive controller uses a neural network model of a nonlinear plant to estimate the plant performance [6]. The controller then calculates the control input that will optimize plant performance over a specified future time horizon. The first step in model predictive control is to determine the neural network plant model (system identification). Next, the plant model is used by the controller to predict future performance.

3.1.System Identification

The first stage of model predictive control is to train a neural network to represent the forward dynamics of the plant. The process is represented by the following figure.3:

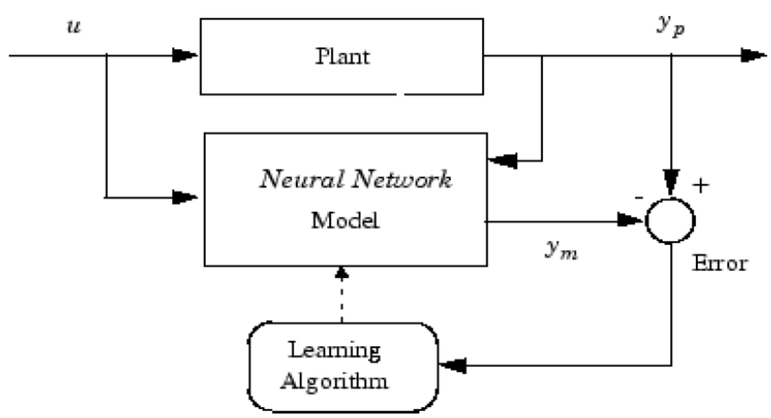

Fig3. The structure of the neural network plant model

The neural network plant model uses previous inputs and previous plant outputs to predict future values of the plant output.

3.2 Predictive Control

The neural network model predicts the plant response over a specified time horizon. The predictions are used by a numerical optimization program to determine the control signal that minimizes performance criterion over the specified horizon.

4.Simulation Results

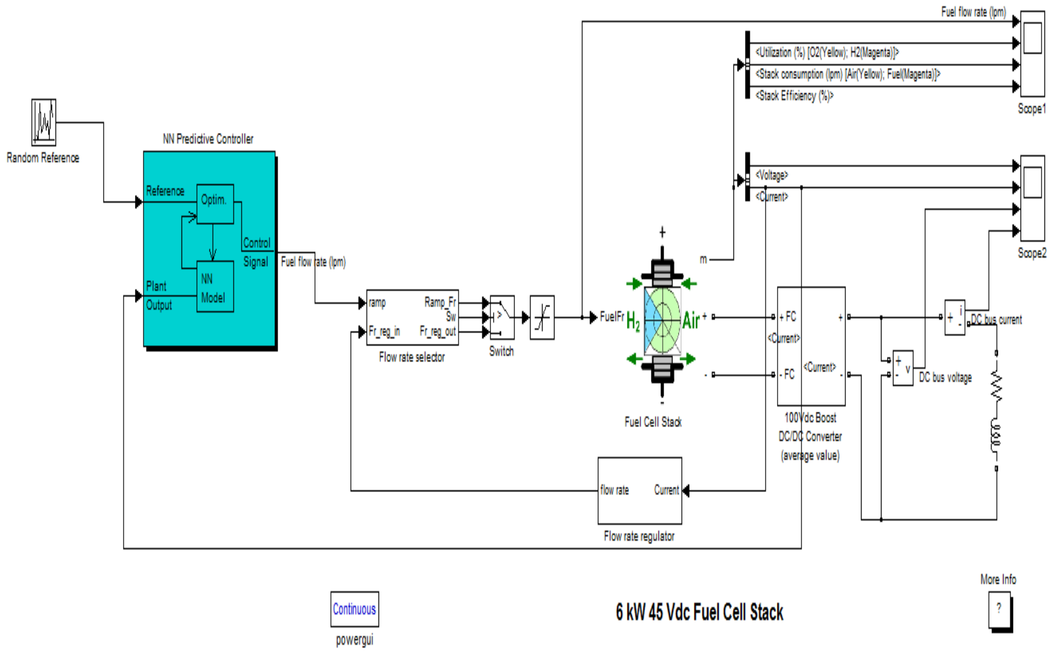

Fig.4.Neural network Controller

The Proton Exchange Membrane (PEM) Fuel Cell Stack model feeds an average value 100Vdc DC/DC converter. The nominal Fuel Cell Stack voltage is 45Vdc and the nominal power is 6kW.This circuit uses a 45Vdc, 6kW PEM Fuel Cell Stack connected to a 100Vdc DC/DC converter. The converter is loaded by an RL element of 6kW with a time constant of 1 sec. During the first 10 secs, the utilization of the hydrogen is constant to the nominal value using a fuel flow rate regulator. After 10 secs, the flow rate regulator is bypassed and the rate of fuel is increased to the maximum value of 85 l pm in order to observe the variation in the stack voltage. That will affect the stack efficiency, the fuel consumption and the air consumption.

4.1.Working

- At t=o sec, fuel flow rate is low & current is high.
- At t=10 sec, fuel flow rate is increased, hydrogen utilization decreases, voltage increases, current decreases hence stack consumption & stack efficiency decreases.
- At t = 0 sec, the DC/DC converter applies 100Vdc to the RL load (the initial current of the load is 0A). The fuel utilization is set to the nominal value of 99.56%. The current increases to the value of 133A. The flow rate is automatically set in order to maintain the nominal fuel utilization. The DC bus voltage

at Scope2 is very well regulated by the converter. The peak voltage of 122Vdc at the beginning of the simulation is caused by the transient state of the voltage regulator

- At t = 10 sec, the fuel flow rate is increased from 50 liters per minute (lpm) to 85 lpm during 3.5 s reducing by doing so the hydrogen utilization. This causes an increasing of the voltage so the fuel cell current will decrease. Therefore the stack consumption and the efficiency will decrease at Scope1.

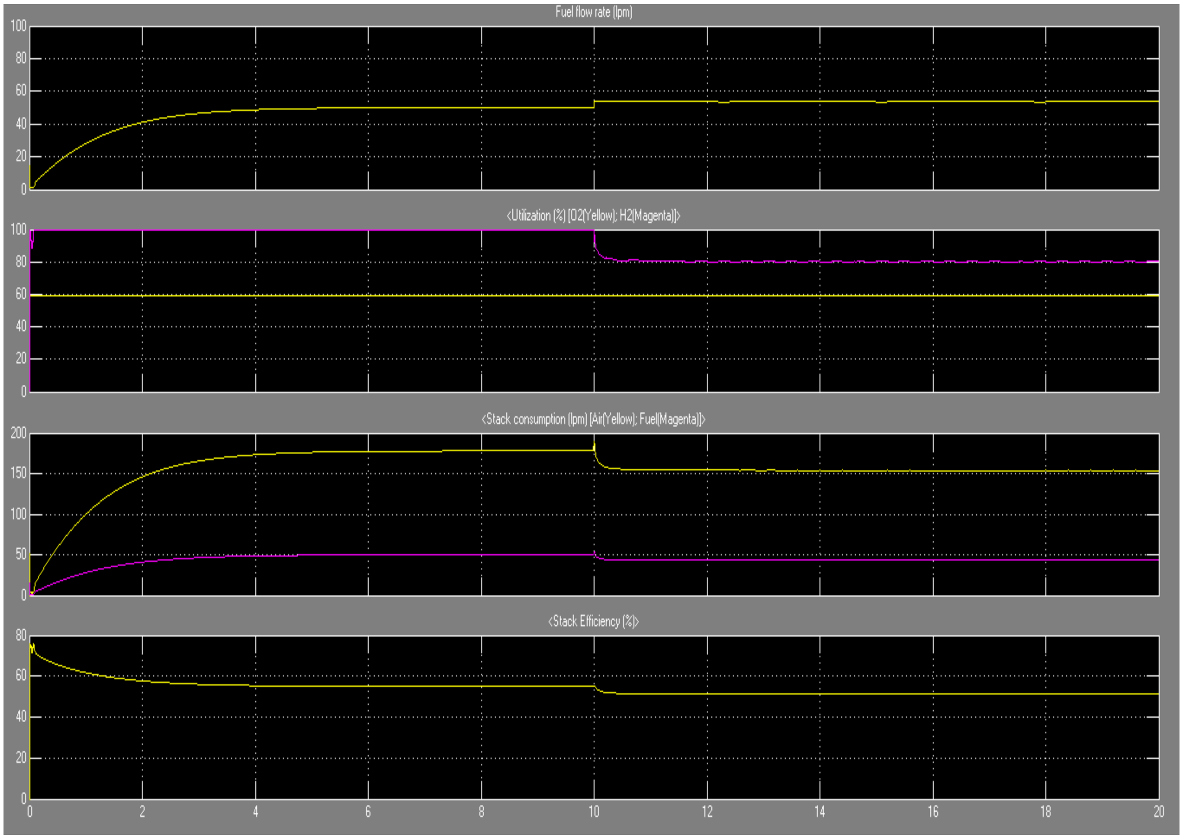

Fig.5.Fuel flow rate Vs Efficiency

5.Conclusion

Transients or variations in loads will damage fuel cell stack and this will affect the fuel cell performance in a very short period. This is because of the delay existing in electrical and mechanical parts of auxiliary equipments such as pumps, heaters and back pressures. Hence, to remove the harmful effect of fast pulse currents, a neural network model along with a NN predictive controller is employed in this study. The control signal is fuel flow rate. The overall system behavior is investigated under random current variations and compare with the fuel cell nonlinear dynamic model. Simulation results show that the proposed neural network model is a fast and proper control system for controlling the fuel cell terminal voltage and improving the system performance. Moreover it will lead to consuming less energy and reducing the control system complexity. The major limitations of this model are chemical reaction dynamics caused by partial pressure changes of chemical species inside the cell are not considered, the stack output power is limited by the fuel and air flow rates supplied, the effect of temperature and humidity of the membrane on the internal resistance is not considered, the flow of gases or water through the membrane is not considered

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