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Proton Exchange Membrane Fuel Cell control using a Predictive control based on Neural Network

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***Abstract*— The PEMFC control system influences the cell performance greatly. Traditional controllers couldn't lead to acceptable responses because of time- change, long- hysteresis, uncertainty, strong- coupling and nonlinear characteristics of PEMFCs, So an intelligent or adaptive controller is needed. In this paper a neural network predictive controller have been designed to control the voltage of at the presence of fluctuations. The results of implementation of this designed NN Predictive controller on a dynamic electrochemical model of a small size 500 W, PEM fuel cell have been simulated by MATLAB SIMUlINK and compared with a traditional PID controller.**

***Index Terms*— fuel cell, PEMFC, neural network, model predictive control.**

I. Introduction

Non-polluting energy generation and other environmental consequences have been driving an increasing demand for new energy conversion technologies during the last few years .Within such perspective fuel cells (FC) have been appeared as an ideal alternative because of their high generation efficiency , high generation power density , no-noise ,zero pollution , module type structure and high reliability and durability. Proton Exchange Membrane Fuel cell (PEMFC) is a kind of fuel cells that directly transforms chemical energy of hydrogen and oxygen into electrical energy through electrochemical reactions without burning and has some other special advantageous made it a great alternative for automotive and movable applications. Cold starting, low temperature operation and non electrolyte corrosion are some exclusive PEMFC's qualities that have made many great engine manufacturing companies developed PEMFC power used for vehicle one after another[1].

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Because of amending of PEMFC's performance and increasing safety and reliability a satisfying control on PEMFC must be done. Traditional controllers couldn't lead to acceptable responses because of time- change, long- hysteresis, uncertainty, strong- coupling and nonlinear characteristics of PEMFCs. So an intelligent or adaptive controller is needed. In this paper a neural network predictive controller have been designed to control the voltage of fuel cell with varying load and at the presence of fluctuations.

The considered model in this paper predicts the FC stack performance against situations commonly encountered in electrical power generation systems, like insertion and rejection of loads [2]. The voltage of cell is output and the pressure of hydrogen and the load current are inputs. The input fluctuations affect the output voltage greatly and these fluctuations must be controlled.

This paper is arranged as follows : the next section reviews the considered PEMFC's model , section III introduces NN predictive controller and it's justification with the PEMFC's considered model, section IV shows the results of implementation of this designed NN Predictive controller in comparison with a traditional PID controller. Section V is conclusions.

II. An Elecrochemical-Based Fuel Cell

The PEMFC internal electrochemical reaction is the process that combines hydrogen and oxygen over a platinum catalyst to produce water, heat and electricity. The PEMFC mechanism is shown in Fig.1.

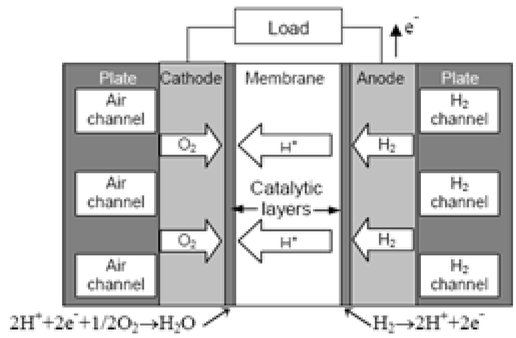

Fig.1 Schematic diagram of PEMFC mechanism

In the presence of the activator-platinum, the molecules of H_2 in anode of PEMFC discharge electrons to lines and become H-ions, meanwhile the molecules of O_2 in the cathode receive the electrons from lines as well as protons from PEM, and so the molecules of water are produced. The electrode reaction equations are as follows:

$$anode(-): H_2 \rightarrow 2H^+ + 2\bar{e} \qquad (1)$$

$$cathode \quad (+): \frac{1}{2}O_2 + 2\bar{e} \rightarrow H_2O \qquad (2)$$

Different mathematical models have been devised to simulate the behavior of PEMFC. Some are based on curve-fitting experiments [3], others are semi-empirical models that combine experimental data with parametric equations adjusted by comparison with cells physical variables like pressure and temperature [4].In both cases, the concentration over-potential phenomenon, which is crucial in describing the dynamical behavior of such systems, is not adequately modeled. The work developed in [5] correctly considers this effect, and for this reason has been adopted as a benchmark for the simulation described in the following.

The output voltage V_{FC} of a single cell can be written as:

$$V_{Fc} = E_{Nenst} - V_{act} - V_{ohmic} - V_{con} \qquad (3)$$

E_{Nenst} is the thermodynamic potential of the cell, which represents the reversible voltage; V_{act} is the activation over-potential, (a measure of the voltage drop associated with the electrodes); V_{ohm} is the concentration over-potential, which takes into account the resistances during conduction of the protons through the solid electrolyte and the electrons through their path; V_{con} is the concentration over-potential, which considers the voltage drop caused by the reduction of concentration of reactants gases or, alternatively, by the transport of masses of oxygen and hydrogen.

$$E_{Nenst} = 1.229 - 0.85\times10^{-3}(T - 298.15) + 4.31\times10^{-5}\,T\left[\ln(P_{H2}) + 1/2\ln(P_{O2})\right] \qquad (4)$$

Where T is the cell operation temperature in [K], P_{H2} and P_{O2} are respectively the hydrogen and oxygen partial pressures in [atm].

$$V_{act} = -[\zeta_1 + \zeta_2 T + \zeta_3 T\ln(C_{O2}) + \zeta_4 T\ln(i_{Fc})] \qquad (5)$$

Where i_{FC} is the cell load current in [A], and ζ 's are the parametric coefficients defined on the basis of kinetic, thermodynamic and electrochemical phenomena [6].

C_{O2} is the concentration of oxygen in the catalytic interface of the cathode (mol/cm3), determined by:

$$C_{o2} = \frac{P_{O2}}{5.08\times10^6 e^{\frac{-498}{T}}} \qquad (6)$$

$$V_{ohmic} = i_{Fc}(R_M + R_c) \qquad (7)$$

Where R_C represent the resistance to the transfer of protons through the membrane, usually considered constant. R_M is the equivalent resistance of the membrane, calculated as:

$$R_M = \frac{\rho_M l}{A} \qquad (8)$$

Where ρ_M is the specific resistivity of the membrane for the electron flow ($\Omega.cm$), A is the cell active area (cm^2) and l is the thickness of the membrane (cm), which serves as the electrolyte of the cell.

$$\rho_M = \frac{181.6\left[1 + 0.03(\frac{i_{Fc}}{A}) + 0.062(\frac{T}{303})^2(\frac{i_{fc}}{A})^{2.5}\right]}{\left[\psi - 0.634 - 3(\frac{i_{Fc}}{A})\right]\times\exp[4.18(\frac{T-303}{T})]} \qquad (9)$$

Where the ψ is an adjustable parameter depending on the relative humidity and stochiometric relation of the anode gas.

$$V_{con} = -B\ln(1 - \frac{J}{J_{max}}) \qquad (10)$$

where B is a parametric coefficient, that depends on the cell and its operation and J represents the actual current density of the cell (A/cm^2).

Using the membrane Nafion 117 with 178µm width the parameters of the stack was used to simulate the control algorithm and the operation conditions are shown in table 1.

TABLE.1 Characteristics of the Electrochemical Model

Parameters	value	parameters	value
T	*343[k]*	ζ_1	*-0.948*
A	$50.6[cm^2]$	ζ_2	$0.0028 + 0.0002\,ln(A) + 4.3\times10^{-5}\,ln(C_{H2})$
P_{H2}	*1[atm]*	ζ_3	7.6×10^{-5}
P_{O2}	*1[atm]*	ζ_4	-1.93×10^{-4}
B	*0.016[v]*	ψ	*23*
R_C	*0.0003 [Ω]*	J_{max}	*1.5A/cm2*
l	*178[µm]*	J_n	*1.2mA/cm2*

The activation and concentration overpotentials can be modeled as first-order delay elements with a time constant $\tau = CR_a$, where C is the equivalent capacitance in [F] and Ra is the equivalent resistace in [Ω].

The value of the capacitance is some few Farads and resitance Ra is determined from the cell output current and the calculated activation and concentration voltages so the time constant τ govering the dynamic is variable with the load conditions.The calculation of the Ra and the effect of the capacitance is determined in fig 2.

The considered model in this paper predicts the FC stack performance against situations commonly encountered in electrical power generation systems, like insertion and rejection of loads. The voltage of fuel cell is output and the pressure of hydrogen and the load current are inputs. Other parameters like temperature and wet considered fix and oxygen partial pressure has been kept equal to half of the hydrogen partial pressure.

III. Neural Network Predictive Controller

NN Predictive Controller is one of the promising strategies for complex FC system. No matter how complicated the system is and in spite of the fluctuations, its desired output can be designated to follow the output of a reference model with specified dynamic. The neural network predictive controller strategy includes the specification of reference model with desired dynamic, on-line parameters estimation and calculation of control signals. The first step in model predictive control is to determine the neural network plant model (system identification). In this stage the prediction error between the plant output and the neural network output is used as the neural network training signal. The process is represented by fig 3.

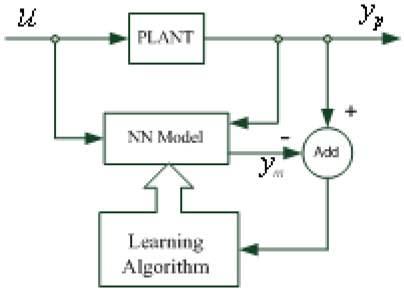

Fig.3Process of NN identification

The neural network plant model uses previous inputs and previous plant outputs to predict future values of the plant output. This feed forward network has one hidden layer and can be trained offline in batch mode, using data collected from the operation of the plant, any of training algorithms in Back Propagation can be used for network training but since our problem is a function approximation and our network has less than a few hundred weights, the Levenberg-Marquardt algorithm will have the fastest convergence. This algorithm is especially noticeable because a very accurate training is required. Levenberg-Marquardt algorithm (trainlm) [7] is able to obtain lower mean square errors and faster convergence than other algorithm tested. (See table II).

Levenbeg-Marquardt uses a nonlinear least squares algorithm to the batch training of the network like other back Propagation algorithms. The performance index for must be minimized is

$$V(\bar{x}) = \sum_{i=1}^{N} e^2{}_i(\bar{x}) \tag{11}$$

Where $e_i(\bar{x})$ is the error between the plant output (yp) and the network output (y_m) for the i_{th} input and $\bar{x}$ is a parameter vector includes all weights and biases that must be updated. For minimizing the performance index with respect to the parameter vector, the Newton's method would be

$$\Delta\bar{x} = -\left[\nabla^2 V(\bar{x})\right]^{-1} \nabla V(\bar{x}) \tag{12}$$

Where $\nabla^2 V(x)$ is the Hessian matrix and $\nabla V(\bar{x})$ is the gradient. It can be shown that

$$\nabla V(\bar{x}) = J^T(\bar{x})\bar{e}(\bar{x}) \tag{13}$$

$$\nabla^2 V(\bar{x}) = J^T(\bar{x})J(\bar{x}) + S(\bar{x}) \tag{14}$$

Where J(x) is the Jacobin matrix and

$$S(\bar{x}) = \sum_{i=1}^{N} e_i(\bar{x})\nabla^2 e_i(\bar{x}). \tag{15}$$

For the Gauss-Newton method it is assumed that S(x)=0 and the update becomes

$$\Delta\bar{x} = \left[J^T(\bar{x})J(\bar{x})\right]^{-1} J^T(\bar{x})e(\bar{x}). \tag{16}$$

The Marquardt-Levenberg modification to the Gauss-Newton method is

$$\Delta\bar{x} = \left[J^T(\bar{x})J(\bar{x}) + \mu I\right]^{-1} J^T(\bar{x})e(\bar{x}). \tag{17}$$

The parameter μ is multiplied by some factor (β) whenever a step would result in an increased *V*(x). When a step reduces *V*(x), μ is divided by β.

The following table compares the performance of different algorithms for modeling the PEMFC by a feed forward Neural Network includes one hidden layer with size=7 and 4000 training data.μ for the starting of trainlm considered 0.01 and β=10.

The Marquardt-Levenberg algorithm can be considered a modification to Gauss-Newton [8].

TABLE.2 Comparision Between Different Algorithms for Network Training to Identify PEMFC

Type	trainbfg	trainrp	traingdx	trainlm
Number of epochs	*34*	*22*	*28*	*18*
Performance index	1.33×10^{-9}	*0.1043*	1.35×10^{-9}	4.9×10^{-10}

The model predictive control method is based on the receding horizon technique. 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 the following performance criterion over the specified horizon

$$\sum_{j=N1}^{N2}(y_r(t+j)-y_m(t+j))^2+p\sum_{j=1}^{Nu}(u'(t+j-1)-u'(t+j-2)) \qquad (18)$$

Where N1,N2 and Nu define the horizons. The u' variable is the tentative control signal, yr is the desired response and ym is the network model response.

IV. Simulation Results

In this section Robustness of proposed controller is proved by simulation of controller in noisy condition and the capability of proposed controller is compared with traditional PID. The voltage of cell is output and the pressure of hydrogen and the load current are inputs. The voltage is a function of load current and pressure and varies with load changing and pressure fluctuations of hydrogen. So a controller is needed to fix voltage at a constant amount.

In the first experiment the control of output voltage and its tracking is tested (fig. 4). Using the data generated from the electrochemical model of PEMFC, a Neural Network described in section III and the predictive controller with cost horizon N2=7, control horizon Nu=2, control weighting factor ρ=0.05 and search parameter α=0.001 results of fig 5 are concluded.

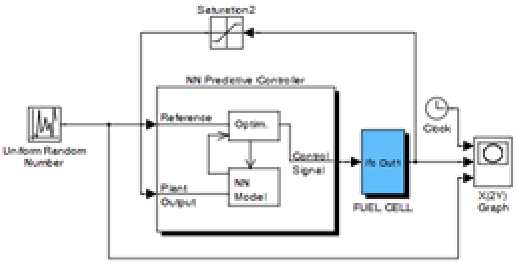

Fig.4 Control of PEMFC voltage by NN Predictive Controller

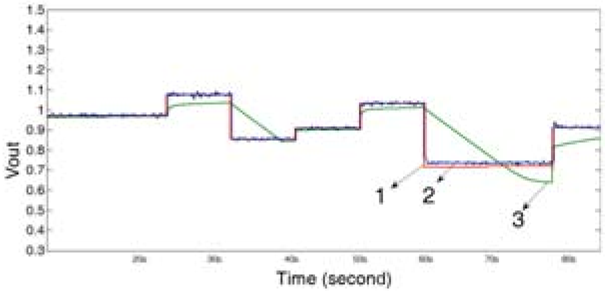

Fig.5 Comparing of tracking operation between PID and NN Predictive Controller: 1-Setpoint Reference, 2-NN predictive response, 3-PID response

Results show that the accuracy and speed of convergence in NN predictive controller is more than PID and the output voltage converges rapidly to the desired output with simple first-order dynamics.

In the other experiment, the NN predictive controller is used as a filter to reduce the effect of noise and fluctuations in the input hydrogen valve.

In noise cancellation, the Neural Network is used to remove noise from signal in a real time. The structure of this method is shown in fig 6.Here, the desired signal d(n) the one to clean up, combines noise and desired information. To remove the noise, a signal n'(n) are fed to the NN filter that represents noise that is correlated to the noise to remove from the desired signal. So long as the input noise to the filter remains correlated to the unwanted noise accompanying the desired signal, the adaptive filter adjusts its coefficients to reduce the value of the difference between y(n) and d(n),removing the noise and resulting in a clean signal in e(n). Notice that in this application, the error signal actually converges to the input data signal, rather than converging to zero.

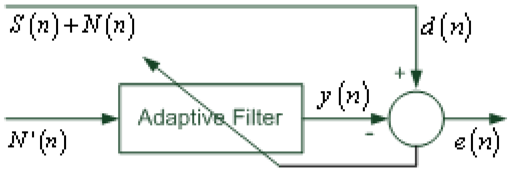

Fig.6 NN as an adaptive filter

Fig 7 shows the output voltage of PEMFC in presence of noise in the pressure of input hydrogen with and without the NN as a filter. It can clearly be seen that the NN filter can reduce the effect of noise in output voltage.

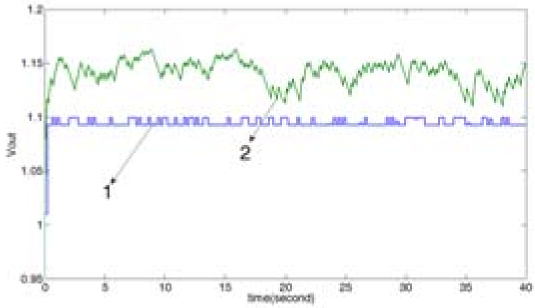

Fig.7 the output voltage of PEMFC in presence of noise and fluctuations: 1-with NN filter, 2-without filter

V.Conclusions

This paper discussed the application of Neural Network Predictive controller to control the output voltage and reduction of noise and fluctuation effects. The dynamic electrochemical model of PEMFC was expressed and used to generate data with current and partial pressure of hydrogen as input and voltage as output. The identification approach was used, based on the single layer feed forward neural network with Levenberg-Marqurdt training algorithm. Simulation results indicate that the performance of NN predictive controller is better than PID and its accuracy and speed of convergence is more. Results also show that this controller can reduce the effect of noise as an adaptive filter.

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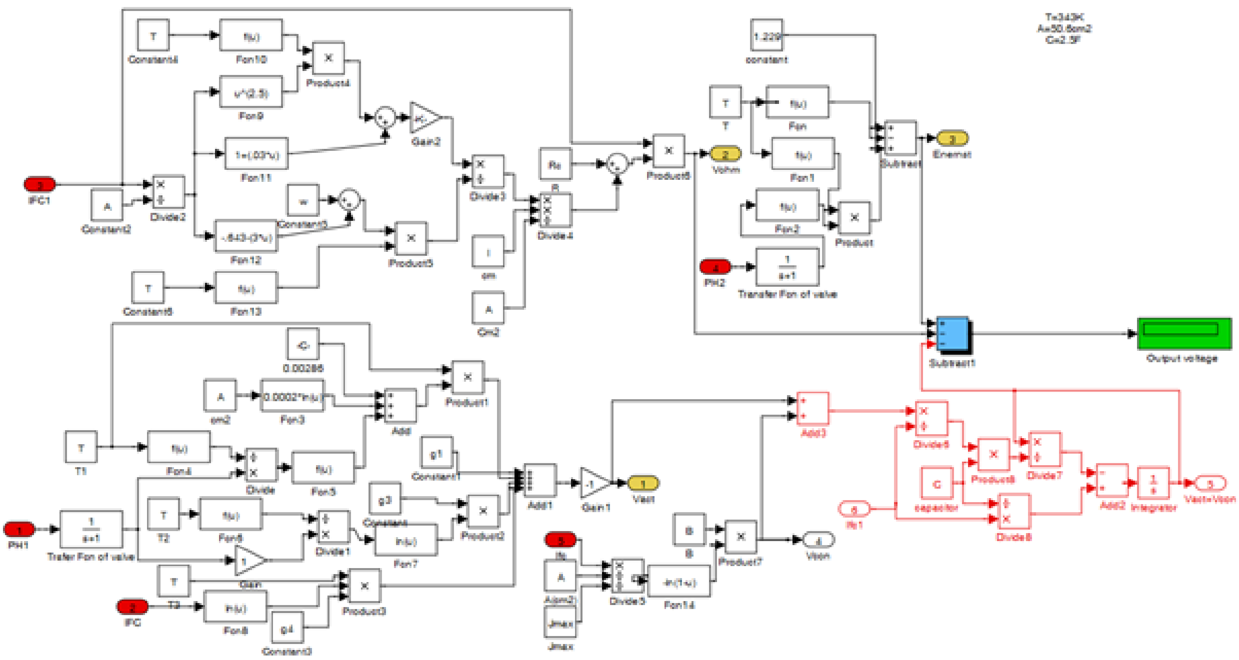

Fig.2 The electrochemical model of PEMFC ,red blocks indicate the first-order delay of Vact and Vcon