MODEL PREDICTIVE CONTROL FOR THE PROTON EXCHANGE MEMBRANE FUEL CELL

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ABSTRACT

Proton exchange membrane fuel cells are promising energy sources that produce electrical currents with almost null pollutant emissions, and they have been received growing attention in recent years. Maintaining a fuel cell system in correct operating conditions requires good system control. Based on the mathematical model of proton exchange membrane fuel cells, model linearization is carried out and a model predictive controller is designed for the proton exchange membrane fuel cell to keep constant voltage output. Simulation results show that the use of this model predictive controller can achieve a good control effect.

Keywords: *Fuel Cell, Model Predictive Control, Linearization Techniques*

1. INTRODUCTION

The world is facing an energy crisis as well as significant environmental problems. It is known that fossil fuels such as petroleum, natural gas and coal are the main resources for generating electricity. However, they also have made a great contribution to environmental problems. Major efforts to reduce greenhouse gas emission have increased the demand for pollution-free energy sources. Non-polluting energy generation and other environmental issues have been driving during the last few years an increasing demand for new energy conversion technologies. Renewable bio-energy is viewed as one of the ways to alleviate the current global warming crisis. Major efforts are devoted to develope alternative electricity production methods (Das and Mangwani, 2010; Logan, 2010).

Fuel cells are promising energy sources that produce electrical currents with almost null pollutant emissions. Proton exchange membrane (PEM) fuel cells are the most popular type of fuel cell (Rezazadeh et al., 2011). PEMFC can be used as emergency power supply and small mobile power supply for outdoors power supply and high reliable and high stable power supply. Besides, in contrast to centralized power supply, PEMFC can be considered as distribution power supply and be gridded into power supply system for peak modulation.

The performance of PEMFC is influenced by many parameters such as operating temperatures both fuel cell and humidifiers, pressure, flow rates and relative humidity of fuel and oxidant gases (Kaytakoglu and Akyalm, 2007). Significant improvements in proton exchange membrane fuel cell technology have been achieved over the past decades. However, the performance, stability, reliability, and cost for the present fuel cell technology are not good enough to replace internal combustion engines. A number of problems must be overcome to improve their performance and reduce their cost (Riascos and Pereira, 2010).

Maintaining a fuel cell system in correct operating conditions requires good system control. Model predictive control (MPC) is an optimization strategy for the control of constrained dynamic systems (Domınguez and Pistikopoulos, 2011). MPC can handle the uncertainty, non-linearity and parallel nature effectively, and can make it easy to deal with the various kinds constraints that exised in the problem of processing controlled variables and manipulated variables. MPC uses multi-step prediction, rolling optimization and feedback to correct control strategies (Holkar and Waghmare, 2011), so it can not only give a good control effect and strong robustness, but also have an advantage of less demand on the accuracy of the model. It is an effective method to solve complex industrial process control (Lee, 2011).

A single proton exchange membrane fuel cell model was built in this paper and a model predictive controller for PEMFC was designed.

2. MATHEMATICAL MODEL OF PEMFC

As an electrochemical energy conversion device, the fuel cell produces electricity from external supplies of fuel (on the anode side) and oxidant (on the cathode side). The outline of a typical PEMFC is illustrated in Fig.1.

In the original hydrogen-oxygen proton exchange membrane fuel cell design, a proton-conducting polymer membrane, which only can be transfered through the proton, and the separation of the anode and cathode sides. On the anode side, hydrogen diffuses to the anode catalyst and then it will be dissociated into protons and electrons. The protons are transfered through the membrane to the cathode, meanwhile, the electrons are forced to travel in an external circuit since the membrane is electrically insulated. On the Cathode catalyst, oxygen molecules react with the electrons (which have traveled through the external circuit) and protons to form water.
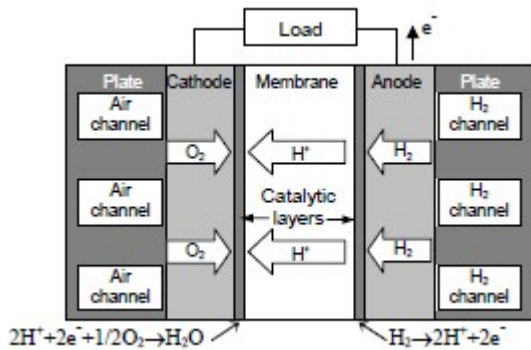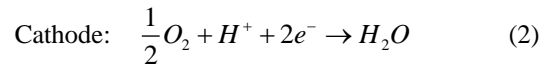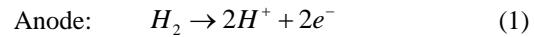

Fig.1 Basic PEMFC Operation

The electric current is produced which is not thermochemical, but electrochemical. Based on the fact that no combustion reactions are involved in there process, there are two obvious advantages over the combustion engines: on the one hand, because of the PEMFC system do not operate with a thermal cycle, their operation is not constrained by the maximum Carnot cycle efficiency as combustion engines are. On the other hand, the PEMFC system run in a clean environment, they do not produce any undesirable products that normally associated with the oxidation of fossil fuels such as CO2, SO2, oxides of nitrogen, or particulate matter, water is the only product.

Mathematical models and simulation are needed as tools for designing the optimization of fuel cells, stacks, and fuel cell power systems. In system studies, it is important to have an adequate model to estimate overall performance of a PEM fuel cell in terms of operating conditions without extensive calculations (Carnes and Djilal, 2005).

PEM fuel cell electrochemical process starts on the anode side where H_2 molecules are brought by flow plate channels. Anode catalyst divides hydrogen on protons H^+ that travel to cathode through membrane and electrons e- that travel to cathode over external electrical circuit. At the cathode hydrogen protons H^+ and electrons e- combine with oxygen O_2 by use of catalyst, to form water H_2O and heat. Described reactions can be expressed by the following equations (Moreira and Silva, 2009; Rezazadeh et al., 2010; Youssef et al., 2010):

$$\text{Anode:} \quad H_2 \rightarrow 2H^+ + 2e^- \quad (1)$$

$$\text{Cathode:} \quad \frac{1}{2}O_2 + H^+ + 2e^- \rightarrow H_2O \quad (2)$$

The output voltage Vfc of a single cell can be defined as the result of the following expression

$$V_{\text{fc}} = E_{\text{nernst}} - V_{\text{act}} - V_{\text{ohmic}} - V_{\text{con}} \quad (3)$$

in which E_{nernst} is the thermodynamic potential of the cell representing its reversible voltage,

$$E_{\text{nernst}} = 1.229 - 0.85 \times 10^{-3}(T_{\text{fc}} - 298.15)$$
$$+ 4.31 \times 10^{-5}T_{\text{fc}}\left[\ln(P_{H_2}) + \frac{1}{2}\ln(P_{O_2})\right] \quad (4)$$

where P_{H_2} and P_{O_2} are the hydrogen and oxygen pressures, respectively, and T_{fc} is the operating temperature. V_{act} is the voltage drop due to the activation of the anode and the cathode:

$$V_{\text{act}} = 0.9514\text{-}3.12 \times 10^{-3}T_{\text{fc}}\text{-}7.4 \times$$
$$10^{-5}T_{\text{fc}}\ln(C_{O_2}) + 1.87 \times 10^{-4}T_{\text{fc}}\ln(i) \quad (5)$$

where i is the electrical current, and C_{O_2} is the oxygen concentration. Vohmic is the ohmic voltage drop associated with the conduction of protons through the solid electrolyte, and electrons through the internal electronic resistance:

$$V_{\text{ohmic}} = i(R_M + R_C) \quad (6)$$

where R_C is the contact resistance to electron flow, and R_M is the resistance to proton transfer through the membrane, which can be described as follows

$$R_M = \frac{\rho_M \cdot l}{A}$$

$$\rho_M = \frac{181.6\left[1+0.03\left(\dfrac{i}{A}\right)+0.062\left(\dfrac{T_{fc}}{303}\right)^2\left(\dfrac{i}{A}\right)^{2.5}\right]}{\left[\psi - 0.634 - 3\left(\dfrac{i}{A}\right)\right]\exp\left[4.18\left(\dfrac{T_{fc}-303}{T_{fc}}\right)\right]}$$

$$(7)$$

where ρ_M is the membrane specific resistivity, l is the membrane thickness, *A* is the membrane active area, and ψ is a specific coefficient for every type of membrane; V_{con} represents the voltage drop resulting from the mass transportation effects, which affects the concentration of the reacting gases and can be described by the following expression:

$$V_{con} = -B\ln(1-\frac{i}{i_{max}}) \qquad (8)$$

where *B* is a constant depending on the type of fuel cell, i_{max} is the maximum electrical current.

Based on the above described mathematical model, a Matlab/simulink simulation model of the PEMFC can be set up (Fan, 2012). Parameters of the Ballard Mark V fuel cell are used in the simulation model (Correa et al., 2004).

3. MODEL LINEARIZATION

The model built above is strongly nonlinear. The high nonlinearity and parameter uncertainty exist in system models make it rather difficult to design a control scheme by using the non-linear model directly. In order to make the controller designed easy, model linearization is an alternative method (Nikolaou and Misra, 2003; Tyner and Lewis, 2010).

The temperature significantly affects the performance of a fuel cell by influencing the water removal and reactants activity, etc (Shan and Choe, 2005; Kirubakaran et al., 2009). It can be seen from Fig.2 that the output voltage decreases as the temperature decreased.

Considering the real work status of PEMFC, the temperature which has powerful effect on the dynamic process, which has been choosen as control variable and other inputs are supposed as constants when linear treatment is done. Then the PEMFC system is linearized to a linear model.
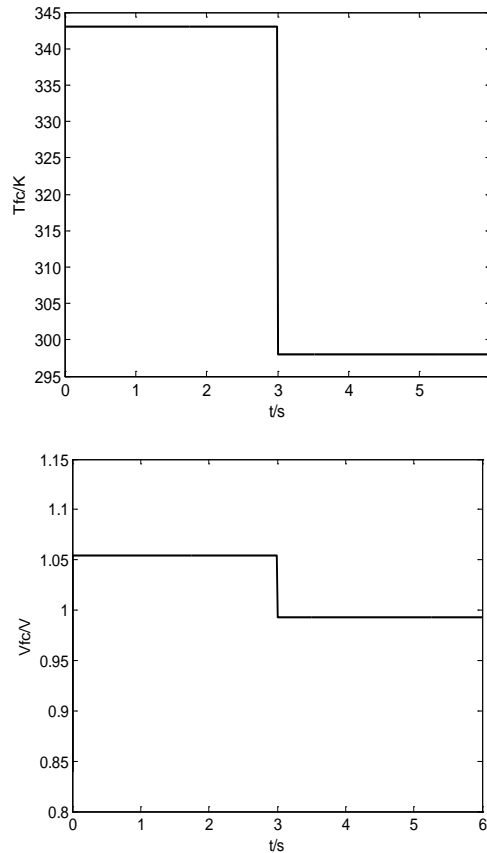

Fig.2. Voltage Changes With Temperature

The PEMFC system has a strong coupling characteristics, so it is difficult to get the linearize model. MATLAB system identification toolbox is used to linearize the model of the PEMFC, and the following linearization model can be derived as:

$$G(s) = \frac{3.0949}{s+0.001} \qquad (9)$$

Simulation responding results of both the linearization model and the nonlinear model to ramp signal $T_{fc}=298+4.5t$ is shown in Fig.3, in which the broken line denotes the linearized model and the solid line stands for the nonlinear model.

It can be seen from Fig.3 that the curve of the linearized model is similar to the curve of the original nonlinear model. In other words, the linearization model can give a valid description of the real system. Thus, the linearization method is regarded as effective and the linearization model can be used instead of the real nonlinear model in designing a MPC controller.
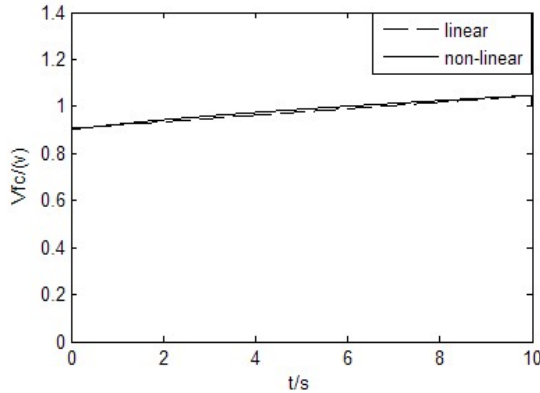
Fig. 3. Simulation Results Of Linearization Model And The Nonlinear Model

4. DESIGN A MPC CONTROLLER

MPC is a form of control in which the current control action is obtained by solving on-line, at each sampling instant, a finite horizon open-loop optimal control problem, using the current state of the plant as the initial state; the optimization yields an optimal control sequence and the first control in this sequence is applied to the plant.

As the unique advanced algorithm model predictive control has been successfully used in industrial areas. The following make contribution to its success:

a)   It handles multivariable control problems naturally.

b)   It can take account of actuator limitations.

c)   It allows operation closer to constraints, hence increased profit.

d)   It has plenty of time for on-line computations.

e)   It can handle non-minimal phase and unstable processes.

f)   It is a regulating convenient way.

The main idea of MPC algorithms is to solve an optimization problem in order to find the control vector trajectory that optimizes the cost function over a future prediction horizon (Jadlovska et al., 2008; Gondhalekar and Jones, 2011; Wang, 2001; Ghasemi, 2011).

Different from the traditional optimal control strategy, the model predictive control uses the non-parametric model based on impulse response as its internal model.

For a given discrete-time systems:

$$x_m(k+1) = A_m x_m(k) + B_m u(k)$$
$$y(k) = C_m x_m(k) \tag{10}$$

The MPC state space model can be expressed as follows:

$$\overbrace{\begin{bmatrix} \Delta x_m(k+1) \\ y(k+1) \end{bmatrix}}^{x(k+1)} = \overbrace{\begin{bmatrix} A_m & O^T \\ C_m A_m & 1 \end{bmatrix}}^{A} \overbrace{\begin{bmatrix} \Delta x_m(k) \\ y(k) \end{bmatrix}}^{x(k)}$$
$$+ \overbrace{\begin{bmatrix} B_m \\ C_m B_m \end{bmatrix}}^{B} \Delta u(k) \tag{11}$$

$$y(k) = \overbrace{[O_m \quad 1]}^{C} \begin{bmatrix} \Delta x_m(k) \\ y(k) \end{bmatrix} \tag{12}$$

which subject to：

$$x_m(k) \in X \subset \mathrm{R}^n, u(k) \in U \subset \mathrm{R}^m$$

where $x_m(k)$ 、 $u(k)$ 、 $y(k)$ are state, input and output vectors, respectively.

Then the predicted expression of x and y can be obtained (suppose in the sampling k_i ($k_i > 0$) :

$$x(k_i + N_P | k_i) = A^{N_P} x(k_i) + A^{N_P-1} B \Delta u(k_i)$$
$$+ B^{N_P-2} \Delta u(k_i + 1) \tag{13}$$
$$+ \cdots + A^{N_P-N_C} B \Delta u(k_i + N_C - 1)$$

$$y(k_i + N_P | k_i) = C A^{N_P} x(k_i) + C A^{N_P-1} B \Delta u(k_i)$$
$$+ C B^{N_P-2} \Delta u(k_i + 1) + \cdots \tag{14}$$
$$+ C A^{N_P-N_C} B \Delta u(k_i + N_C - 1)$$

According to the historical information and the future input, the future control action can be decided and the future output can be predicted by finding the optimal solution of the performance indicator described in the following equation:

$$J(u,k) = \sum_{j=N_1}^{N_2} \hat{x}^{\mathrm{T}}(k+j|k) Q x(k+j|k)$$
$$+ \sum_{j=1}^{N_C} u^T(k+j-1) R u(k+j-1) \tag{15}$$

in which $\hat{x}(k+j|k)$ is the prediction of $\mathrm{x}(k+j)$, $u(k)$ is the process control signal, N_P is the minimum cost-horizon, N_2 is the prediction horizon, Q is the state weighting matrix, N_c is the control horizon, and R is the control weighting matrix.

Based on the knowledge up to time k, the increment input signal is

$$\Delta u(k)=u(k)-u(k-1) \qquad (16)$$

Constraints: If there is more than one input, then the constraints are specified for each input independently. In the multi-input case, suppose that the constraints are given for the upper limits as

$$[\Delta u_1^{max}, \Delta u_2^{max} ..., \Delta u_m^{max}] \qquad (17)$$

and lower limits as

$$[\Delta u_1^{min}, \Delta u_2^{min} ..., \Delta u_m^{min}] \qquad (18)$$

Figure 4 explains the idea of receding horizon. At time k, the future control sequence $\{u(k),...,u(k+N_C-1)\}$ is optimized so that the performance-index $J(u, k)$ is minimized subject to constraints.

At time k the first element of the optimal sequence ($u(k)$) is applied to the real process.

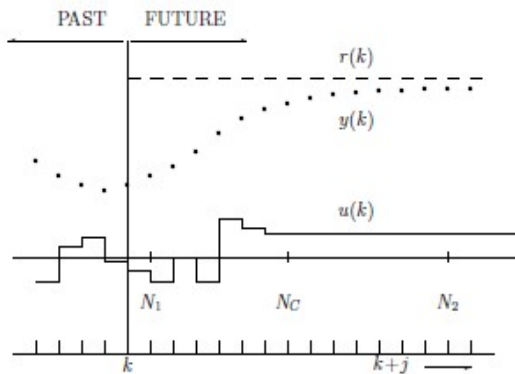At the next time instant, the horizon is shifted and a new optimization at time $k+1$ is solved.

Fig.4. Moving Horizon In Predictive Control

The specific optimization process of predictive control is: each time when samples, it corrects predictive output based on model via output voltage actually measured and then conducts new optimization. It forms a closed loop optimization which not only used model information but also feedback information.

5. SIMULATION AND RESULTS ANALYSIS

The Simulink simulation model of the MPC control based on the linear model of the PEMFC is shown in Fig.5. The blcok "PEMFC" consists of a series functions according Equ. 3 to Equ. 8. Firstly, the PEMFC system is established to run and analyze. Secondly, the model predictive controller is designed and debugged. At last, the model predictive applied to the PEMFC for debugging and runing.

Control parameters of MPC are confirmed by trial and error. The control time interval is Tint=0.01s, the predictive region length is NP=20, the control region length is Nc=4, the robustness and rapidity are 0.8, the input weight is 0.0001, the weight change rate is 0.01, the output weight is 1, the measurable disturbance v=0, and the input constrain is [293, 380], the output constraints value is [0, 2]. Output noise interference is not considered for the time being. In order to get the final accurate answer, every parameter should be analyzed and compared according to the output voltage curve.
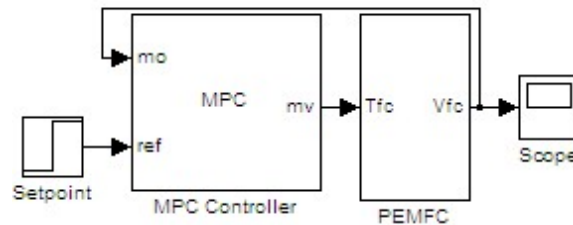

Fig. 5. Simulation Model Of MPC Control

Simulation results are shown in Fig.6 to Fig.8, in which hygrogen pressure, oxygen pressure and load has a sudden change at 5s respectively. The given output voltage is 1.05V. It can be seen from these figures that MPC can make the output voltage of PEMFC follow the given output voltage signal well, no matter how the hydrogen pressure, oxygen pressure or the load changes.
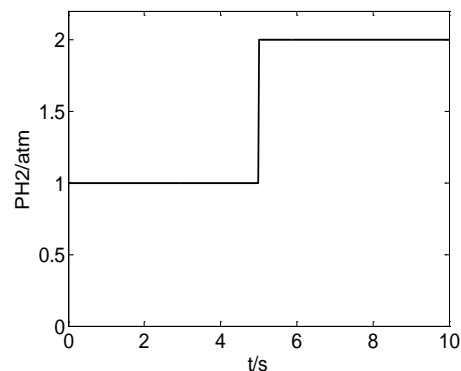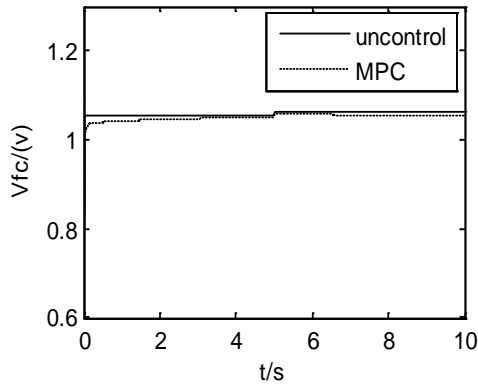
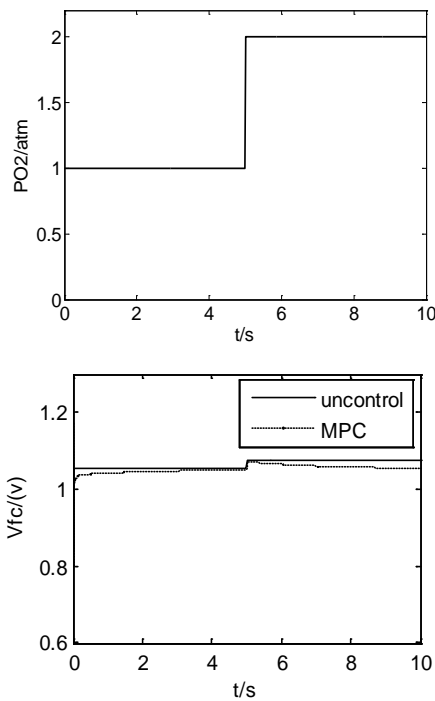*Fig.6. Output Curves Corresponding To Hygrogen Pressure Changing*

Fig. 7. Output Curves Corresponding To Oxygen Pressure Changing
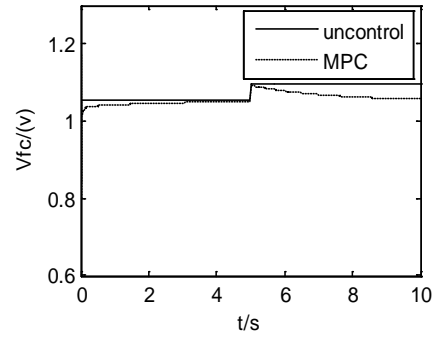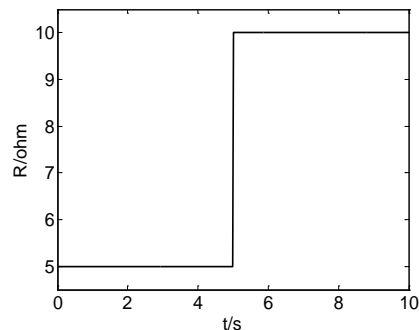

Fig.8. Output Curves Corresponding To Load Changing

6. CONCLUSIONS

The model predictive controller for PEMFC can be designed conveniently by the method of model linearization. By using MPC controller to the PEMFC, the system can not only have fast response characteristic, but also have good steady-state behavior and strong robustness. The designed model predictive control scheme can get satisfactory results as long as choosing reasonable parameters for the controller. The next work is to use model predictive controllers to a real fuel cell system, and further study will be needed to improve the output power of the PEMFC.

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REFERENCES

[1] Carnes, B. and N. Djilal, 2005. *Systematic parameter estimation for PEM fuel cell models.* J. Power Sources, 144(1): 83–93.

[2] Correa, J. M., F. A. Farret, L. N. Canha and M. G. Simoes, 2004. An Electrochemical-based fuel-cell model suitable for electrical engineering automation approach. IEEE T. Ind. Electron., 51(5): 1103-1112.

[3] Das, S. and N. Mangwani, 2010. *Recent development of microbial fuel cell: a review. J. Sci. Ind. Res.*, 69(1): 727-731.

[4] Domınguez, L. F. and E. N. Pistikopoulos, 2011. *Recent advances in explicit multiparametric nonlinear model predictive control. Ind. Eng. Chem. Res.*, 50(2): 609-619.

[5] Fan, L. P., 2012. *Simulation study on the influence factors of generated output of proton*

exchange membrane fuel cell. AMM, 121-126: 2887-2891.

[6] Ghasemi, A., 2011. *Application of linear model predictive control and input-output linearization to constrained control of 3D cable robots*. Mod. Mech. Eng., 1(2): 69-76.

[7] Gondhalekar, R. and C. N. Jones, 2011. *MPC of constrained discrete-time linear periodic systems - a framework for as*ynchronous control: strong feasibility, stability and optimality via periodic invariance. Automatica, 47(2): 326-333.

[8] Holkar, K. S. and L. M. Waghmare, 2010. *An overview of model predictive control. SERSC. Int. J. Contr. Auto.*, 3(4): 47-63.

[9] Jadlovska, A., N. Kabakov and J. Sarnovsky, 2008. *Predictive control design based on neural model of a non-linear system. ACTA Polytech. Hung*., 5(4): 93-109.

[10] Kaytakoglu, S., and L. Akyalm, 2007. *Optimization of parametric performance of a PEMFC*. Int. J. Hydrogen. Energ., 32(17): 4418-4423.

[11] Kirubakaran, A., S. Jain and R.K. Nema, 2009. *The PEM fuel cell system with DC/DC boost converter:* design, modeling and simulation. IJRTE, 1(3): 157-160.

[12] Lee, J., 2011. *Model predictive control: review of the three decades of development.* Int. J. Control. Autom., 9(3): 415-424.

[13] Logan, B. E., 2010. *Scaling up microbial fuel cells and other bioelectrochemical systems.* Appl. Microbiol. Biot., 85(6):1665–1671, 2010.

[14] Moreira, M. V. and G. E. Silva, 2009. *A Practical Model for Evaluating the Performance of Proton Exchange Membrane Fuel Cells*, Renewable Energy, 34(7): 1734-1741.

[15] Nikolaou, M. and P. Misra, 2003. *Linear control of nonlinear processes: recent developments and future directions.* Comput. Chem. Eng., 27(8-9): 1043-1059.

[16] Rezazadeh, A., A. Askarzadeh and M. Sedighizadeh, 2011. *Adaptive inverse control of proton exchange membrane fuel cell using RBF neural network, Int. J. Electrochem. Sci*., 6: 3105-3117.

[17] Rezazadeh, A., M. Sedighizadeh and M. Karimi, 2010, *Proton Exchange Membrane Fuel Cell Control Using a Predictive Control Based on Neural Network*, International Journal of Computer and Electrical Engineering, 2(1): 81-85.

[18] Riascos, L. A. M. and D. D. Pereira, 2010. *Controlling operating temperature in PEM Fuel Cells.* ABCM Sym. Ser. in Mech., 4: 137-146.

[19] Shan, Y. S. and Y. Choe, 2005. *A high dynamic PEM fuel cell model with temperature effects. J. Power Sources,* 145(1): 30–39.

[20] Tyner, D. R. and A. D. Lewis, 2010. *Geometric Jacobian linearization and LQR theory*. J. Geom. Mech., 2(4): 397–440.

[21] Wang, L., 2001. *Continuous time model predictive control design using orthonormal functions.* Int. J. Contr, 74(16): 1588-1600.

[22] Youssef, M. E., K. E. NAdi and M. H. Khalil, 2010. *Lumped Model for Proton Exchange Membrane Fuel Cell (PEMFC)*, International Journal of Electrochemical Science, 5: 267-277.