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Adaptive Inverse Control of Proton Exchange Membrane Fuel Cell Using RBF Neural Network

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Proton exchange membrane fuel cells (PEMFCs) present remarkable control demands, due to the inherent nonlinear characteristics and time-varying parameters. This paper deals with the application of adaptive inverse control using radial basis function neural network (RBFNN) to PEMFC system. This control scheme has the advantage of not needing to identify the dynamical parameters of the system for design and scheduling of the controller parameters. In order to improve the control aim and to guarantee the closed loop stability as well as system's robustness a feedback PD controller is combined with the RBF-based adaptive inverse control. Results from the simulation manifest that the inverse control scheme is promising technique and can ensure the satisfactory performance.

Keywords: Proton exchange membrane fuel cell system, adaptive inverse control, radial basis function neural network.

1. INTRODUCTION

Fuel cells are silent devices that can provide power to a wide variety of applications. Although they have many resemblances with the batteries, in contrast with them, to maintain the power output, fuel has to be always provided to the cell while a typical battery stores the chemical energy [1]. The fuel which is commonly used in fuel cells is hydrogen but there is another type of fuel cell known as direct-mode bioorganic fuel cell (DMBFC) in which the fuel glucose and an aqueous electrolyte are mixed with each other. In the DMBFC the current densities are very low in comparison to current densities of several hundred $mAcm^{-2}$ in the direct fuel cells, which are supplied with either hydrogen or alcohols [2, 3]. However, the DMFC is simple to use and provides good application potentials for both small portable equipment and large systems.

Due to high efficiency and low aggressions to the environment, Fuel cells as one of the most promising sources of electric power have been actively regarded by electric companies. Since there is no combustion in fuel cell systems, they can produce electricity with minimal pollutant. Proton exchange membrane fuel cell (PEMFC), as the most popular kind of fuel cells in the residential and vehicular applications, when is compared with the other fuel cells, is able to efficiently generate high power densities. PEMFC operates at low temperatures and its start up is fast as well as has zero emission if it is run with pure hydrogen.

Because of low voltage and high current output characteristic of the fuel cell generation system, the system performance is very sensitive to load variations, so the control system should compensate this by making the output voltage as constant as possible. PEMFC is an uncertain nonlinear system and with the change in operating point, its parameters vary. Because it is very hard to gain perfect dynamic model for the PEMFC, model-based controllers actually result no better performance that of the conventional fixed gain controllers. Control task is also more difficult if we consider all the fuel cell generation plant that comprises also many nonlinear subsystems interacting with others. Therefore, the controller should be robust to uncertainty and assure control objectives.

Neural networks as efficient tools for identification and control of unknown systems have proved themselves in many investigations due to handle complex input-output mapping without detailed analytical model of the system. Interesting attention has been made via authors to identify and control of fuel cells by neural networks in recent years. To improve robustness a model-predictive controller (MPC) with an on-line neural network identifier for the air stream and hydrogen flow with recirculation in a PEMFC system have been designed by Bao et al in [4]. Paulo et al in [5] to control the output voltage of a proton exchange membrane fuel cell by parametric cerebellar model articulation controller (P-CMAC) have proposed a new approach to design neural optimal control systems. Cirrincione et al in [6] have investigated the application of non-linear predictive control with neural networks to regulate the cell voltage, acting on the hydrogen pressure, trying to reduce the variation of the input control variable. Tao et al in [7] have used the approach and self-study ability of artificial neural networks to build the model of the nonlinear system, and uses the adaptive neural-networks fuzzy infer system (ANFIS) to build the temperature model of PEMFC, which is used as the reference model of the control system, and adjusts the model parameters to control it online. Narendra et al in [8] have developed an adaptive control using neural networks and approximate models, which achieved a good performance of the controller. In the control of hydrogen utilization in fuel processors of fuel cell vehicles Iwan in [9] has been applied neural network.

In this paper, a radial basis function neural network-based (RBFNN) adaptive inverse control strategy as a feed-forward controller for voltage control of PEMFC system by acting on the methane flow rate is presented. In this way, a RBF neural network with Gaussian neurons is used to identify the inverse model of PEMFC system. To generate control signal this on-line inverse model identifier is used as a feed-forward controller and to insure closed loop stability and system's robustness is combined with a feedback PD controller. This control design is reliable and efficient that can overcome on the main problems such as the time-varying parameters, nonlinearity and uncertainties of the PEMFC system which during the optimal control of fuel cell, designer may be faced with them. In addition, the robustness of the control system is validated by applying the additive noise to the PEMFC system.

The main body of this paper is organized as follows. In section 2, to execute design and analysis of adaptive inverse control, a dynamic PEMFC system mathematical model is introduced. Adaptive inverse control strategy is discussed in section 3. Section 4 explains the RBF networks and adaptation rule. In section 5, the simulation results are given. Finally, the conclusion is stated in section 6.

2. PEMFC SYSTEM DYNAMIC MODEL

The major components of a PEMFC system are fuel processing unit or reformer and the fuel cell stack. Generally, by processing some hydrogen-containing fuels such as methanol, ethanol, or natural gas in the reformer hydrogen fuel is provided and is supplied to the stack.

Today there are a great number of models in literature, which have been invented by researchers to indicate the accurate representation from PEMFC system internal behavior. Majority of the proposed models are based on fluid dynamics, electrochemical reaction, heat transfer and thermal [10−14]. In continue one of the most influential PEMFC system dynamic models is concisely introduced. This model has been employed for the simulations. The model parameters are as follows:

B, C	Constants to simulate the activation overvoltage in PEMFC (A^{-1}) and (V).
CV	Conversion factor (kmol hydrogen/kmol methane)
E_0	Standard no load voltage (V)
F	Faraday's constant (C/kmol)
I	Stack current (A)
K_r	Modeling constant (kmol/s A)
K_{H_2}	Hydrogen valve molar constant (kmol/atm s)
K_{H_2O}	Water valve molar constant (kmol/atm s)
K_{O_2}	Oxygen valve molar constant (kmol/atm s)
N_0	Number of series fuel cells in the stack
p_{H_2}	Hydrogen partial pressure (atm)
p_{H_2O}	Water partial pressure (atm)
p_{O_2}	Oxygen partial pressure (atm)
q_f	Methane flow rate (kmol/s)
q_{H_2}	Input molar flow of hydrogen (kmol/s)
q_{O_2}	Input molar flow of oxygen (kmol/s)

r_{H-O}	Hydrogen-oxygen flow ratio
R	Universal gas constant (1atm/kmol K)
R^{int}	Stack internal resistance (Ω)
T	Absolute temperature (K)
V_{cell}	Dc output voltage (V)
τ_f	Reformer time constant (s)
τ_{H_2}	Hydrogen time constant (s)
τ_{H_2O}	Water time constant (s)
τ_{O_2}	Oxygen time constant (s)

2.1. Reformer model

A simple model with a second-order transfer function for a fuel-processing unit that produces hydrogen through reforming methane is developed by author in Ref. [15]. Ref. [16] indicates that fuel process approximated by a first-order transfer function is appropriate for simulation point of view. Therefore, the mathematical form of the model can be represented by the following formula:

$$\frac{q_{H_2}}{q_f} = \frac{CV}{\tau_f s + 1} \qquad (1)$$

Using the hydrogen-oxygen flow ratio, oxygen flow can be acquired. The model of reformer is sketched in Fig. 1.

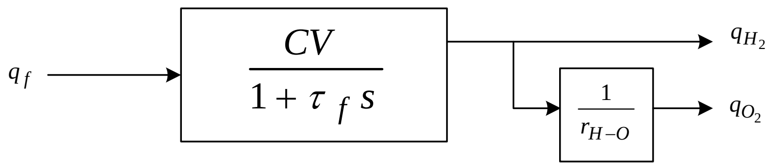

Figure 1. Reformer model block diagram

2.2. PEMFC model

A model for SOFC system is developed by Padulles et al in Ref. [14]. To simulate a PEMFC this model is modified in Ref. [13]. The model is capable to illustrate the output voltage as a function of partial pressures of hydrogen, oxygen, and water. Block diagram of the PEMFC model is depicted in Fig. 2.

When a PEMFC system is operating, if the load current change, accordingly the stack voltage will be decreased or increased. The methane flow rate can affect on the stack voltage so that by ascending the methane flow rate, voltage will be raised and vice versa. Therefore, to maintain the stack voltage in reference value the methane flow rate can be controlled. The control aim in our study is to adjust the stack voltage at the reference value by acting on methane flow rate as the control signal.

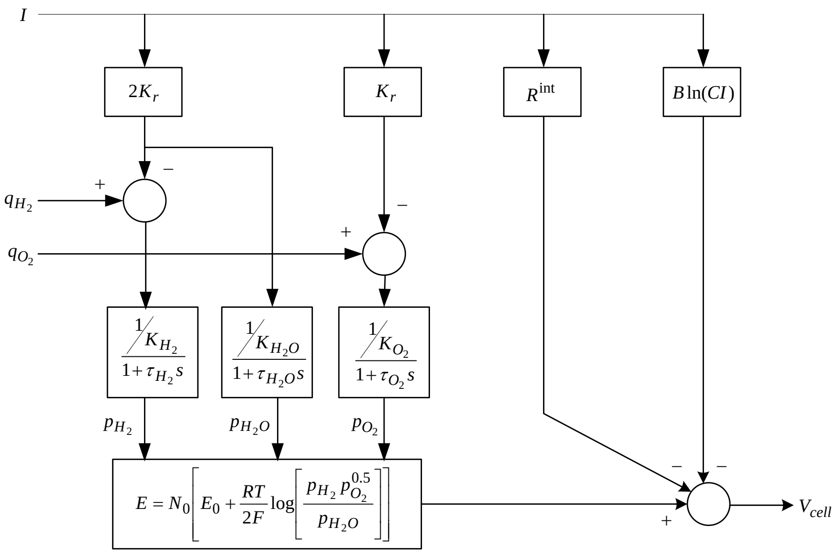

Figure 2. PEMFC model block diagram

3. ADAPTIVE INVERSE CONTROLLER STRATEGY

In the most control goals, the plant to be controlled may be time variable and uncertain. Adaptive control systems for such plants as compared to fixed systems have many advantages due to adjusting their parameters during operation.

The main goal of inverse control is to gain the plant via a signal from controller that when is placed in series with the actual plant the plant forward system is eliminated ($F^{-1}F = 1$). PEMFC is an uncertain nonlinear system and with the change in operating point, its parameters vary. Therefore, its control is very difficult task. Therefore, the controller should be robust to uncertainty and assure control aims. In this research, a radial basis function neural network (RBFNN) is used as an inverse system identifier, and then the network is placed in series with PEMFC system and to improve the performance of control scheme, a feedback PD controller is added to the RBF-based inverse controller. Block diagram of PEMFC system and its controller is shown in Fig. 3.

The input of RBF-based inverse controller is the reference value and the output voltage as the system output is compared with the reference value and is fed to feedback controller. Sum of inverse controller output q_f^{nn} and feedback controller output q_f^{pd} make the control signal, which is supplied to the system.

$$q_f = q_f^{pd} + q_f^{nn} \qquad (2)$$

If the inverse model of PEMFC system is well-identified, necessary control signal for the system to track the reference voltage will be provided alone via inverse controller and the output of feedback controller will have a tendency to zero. Therefore, in generating the control signal, the main role is played by inverse controller. Here, the feedback controller output is used for adjusting the network weights. Network weights change as long as the feedback controller output falls to the acceptable minimum value. The inverse model of fuel cell is placed in series with the actual system after satisfactory training so that the PEMFC system forward model is eliminated and the output voltage follows the reference value.

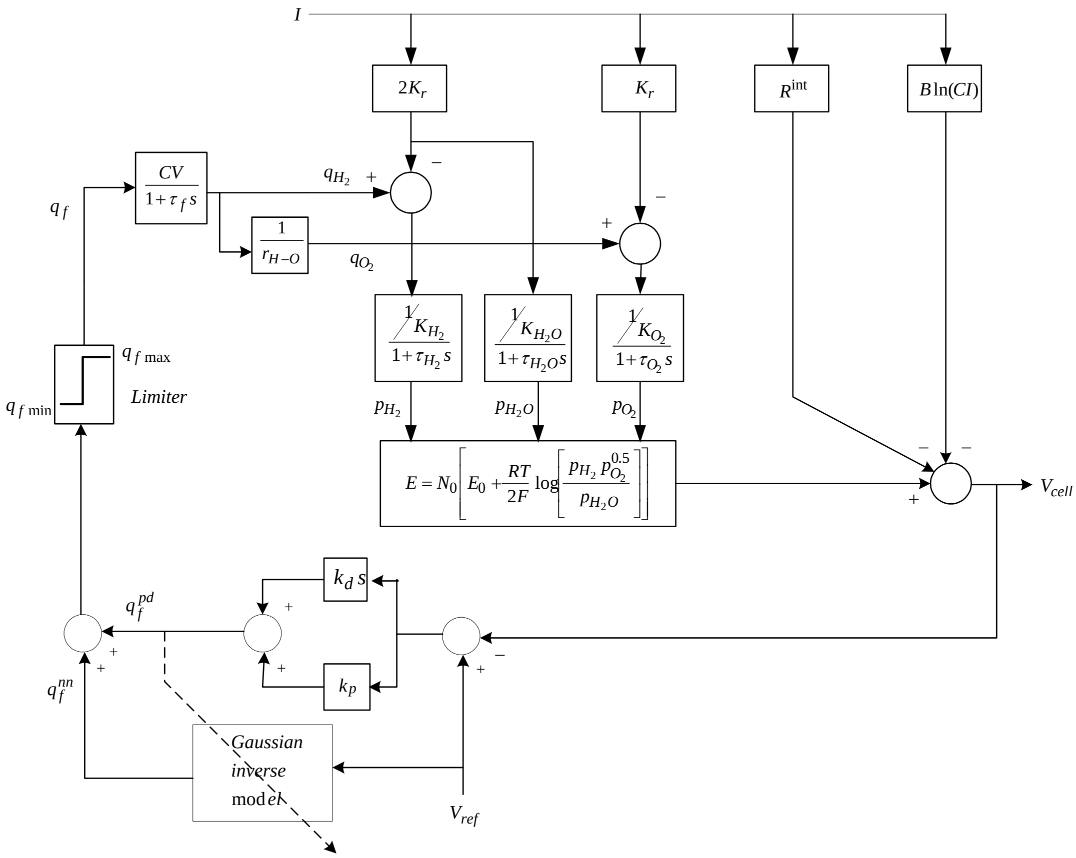

Figure 3. PEMFC system and controller block diagram

4. RBF NEURAL NETWORK

Artificial neural networks (ANNs) due to superior capability have been used to control of unknown and uncertain systems. Neural networks as powerful tools to identify, can learn and adapt themselves with environment variations and approximate each function with any degree of precise.

RBFNN with variety of applications is one of most popular neural networks and probably the main rival of feed forward back-propagation (FFBP) neural networks. The superior performance of RBFNN over FFBP neural networks to identify has been shown by authors in [17]. RBFNN is made in its most basic form, from three layers with entirely different roles. The input layer that connects the network to its environment is made up of source nodes. In the second layer, the solely hidden layer in the network, a nonlinear transformation is made from the input space to the hidden space. The output layer is linear supplying the answer of the network to the activation pattern applied to the input layer [18]. In this paper, we make use of one RBFNN with Gaussian neurons in hidden layer to identify the inverse model of PEMFC system.

Let us consider the following definitions:

$$W = [w_j], \qquad j = 1,2,\ldots,N_h \tag{3}$$

where W is a vector of output weights and N_h is the number of hidden neurons.

$$\Phi = [\phi_j], \qquad j = 1,2,\ldots,N_h \tag{4}$$

where Φ is a vector of gaussian-shaped regressors which here are defined by:

$$\phi_j = \exp\left(-\frac{\left\|V_{ref} - c_j\right\|^2}{2b_j^2}\right) \tag{5}$$

where V_{ref} is reference value, b_j and c_j are the width and center of hidden units, respectively. The network output $Y(q_f^{nn})$ can be expressed by:

$$Y = W \times \Phi^T \tag{6}$$

According to Lyapunov analysis of stability, adaptation law for adjusting network weights has been developed by authors in Ref [19]. This weight adaptation law is simplified and is used to adjust RBF weights. Equation (7) defines the weight adaptation law.

$$\dot{W} = \gamma \times q_f^{pd} \times \Phi \tag{7}$$

where $\gamma < 1$ is a positive constant controlling adaptation speed. The appropriate selection of γ insure system's stability.

5. SIMULATION RESULTS

The behavior of PEMFC system and controller structure has been simulated in Matlab environment. The optimum structure of RBF network is found by trial and error. The number of Gaussian neurons is obtained at 21. The adaptation speed is set at 0.03 and the reference voltage is set at 53 V. Proportional and derivative gains of the PD controller is selected 0.001 and 3, respectively. The parameters used for this simulation, from a 5 KW commercial PEMFC [20], are given in Table 1.

Table 1. Model parameters

Parameter	Value	Parameter	Value
B	0.04777 A^{-1}	q_f^{max}	0.00025 kmol/s
C	0.0136 V	q_f^{min}	0.00005 kmol/s
CV	1	r_{H-O}	1.168
E_0	0.6 V	R	8314.47 J/(kmol K)
F	96484600 C/kmol	R^{int}	0.00303 Ω
$K_r = \frac{N_0}{4F}$	2.2802e-7 kmol/(s A)	T	343 K
K_{H_2}	4.22e-5 kmol/(atm s)	τ_f	5 s
K_{H_2O}	7.716e-6 kmol/(atm s)	τ_{H_2}	3.37 s
K_{O_2}	2.11e-5 kmol/(atm s)	τ_{H_2O}	18.418 s
N_0	88	τ_{O_2}	6.74 s

The PEMFC system displayed in Fig. 3 is tested with step changes in the load current as Fig. 4. Adaptive inverse controller is used to adjust the terminal voltage at reference value. The simulation results indicate clearly that control system behaves correctly. As Fig. 5 shows, in all times the output voltage follows the reference value. Fig. 6 and Fig. 7 represent the curve of tracking error and control signal, respectively. In some instants, the value of methane flow rate exceeds the limits. Then the flow rate saturates to the limiter value. As it is mentioned before if the inverse model of PEMFC system is well identified the main role in generating the control signal is played by inverse controller. If we regard to the generated control signal by two controllers, for example in the last step when the current changes from 70 to 90 A in the steady the generated control signal by RBF- based inverse controller is 2.25e-4 Kmol/s while PD controller produces only 1.82e-9 Kmol/s. It is obvious that the inverse model of PEMFC system is well identified by RBF network.

In addition, in present research the performance of control system against added noise to the load current and output voltage is investigated in order to check the robustness of the controller. The noisy data are derived by adding a random distribution with a mean of 0 and a variance of σ^2. Fig. 8 shows the variation of noisy load current (with variance 1%). Performance of control system against the added noise is indicated in Fig. 9. As can be seen, the output voltage is close to the desired value, even if there is an additive noise.

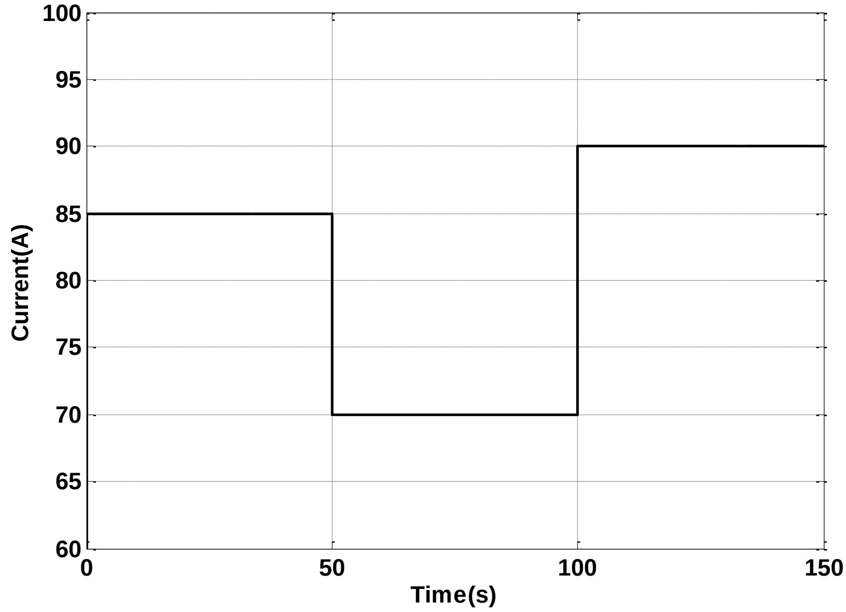

Figure 4. Variations of load current

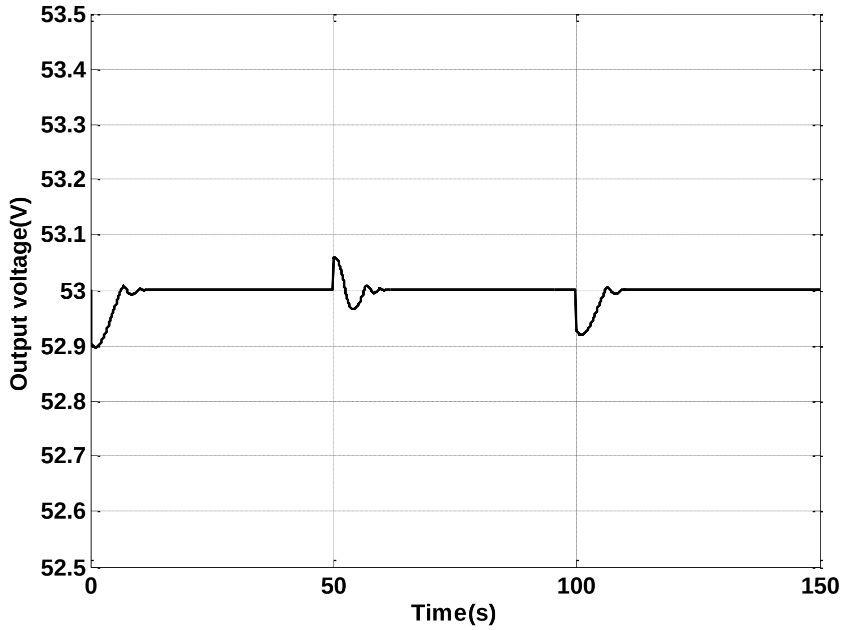

Figure 5. Curve of output voltage by control system

As a further test, noise is added to the output voltage and the controller performance is considered. Fig. 10 shows the variation of applied load current and the performance of controller against the added noise is shown in Fig. 11. The control precision in the presence of noise (with standard deviation 0.2%) is acceptable in engineering.

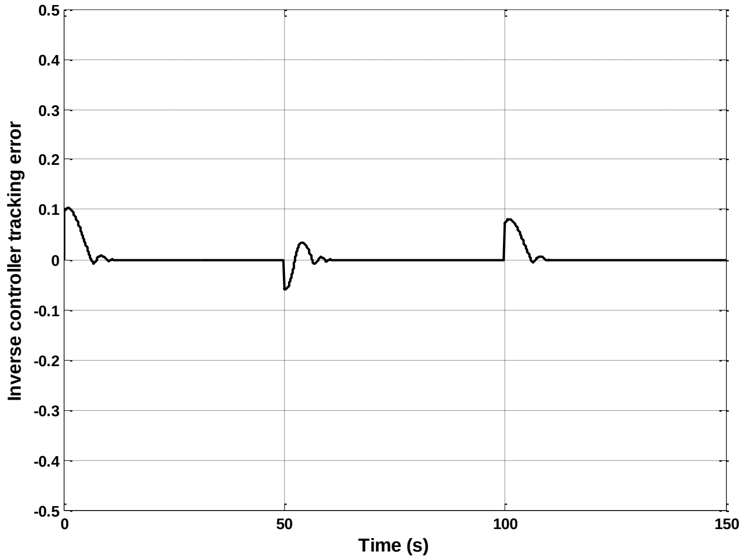

Figure 6. Curve of tracking error

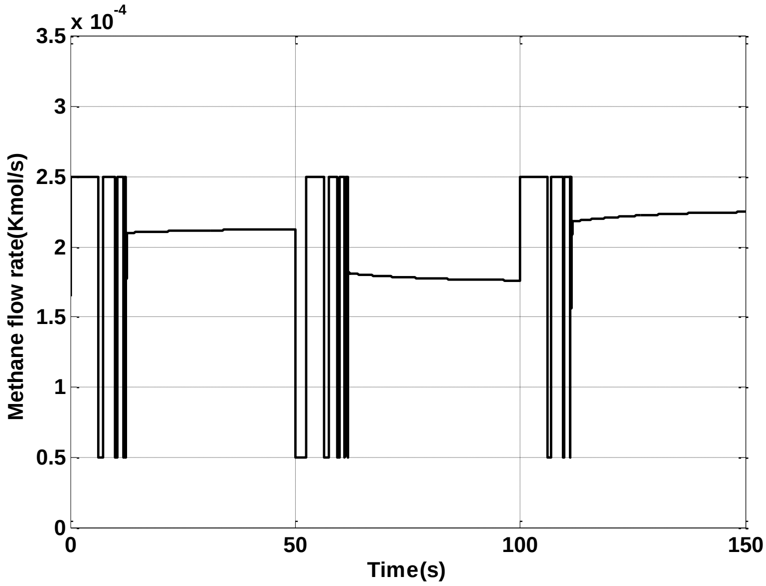

Figure 7. Curve of methane flow rate as control signal

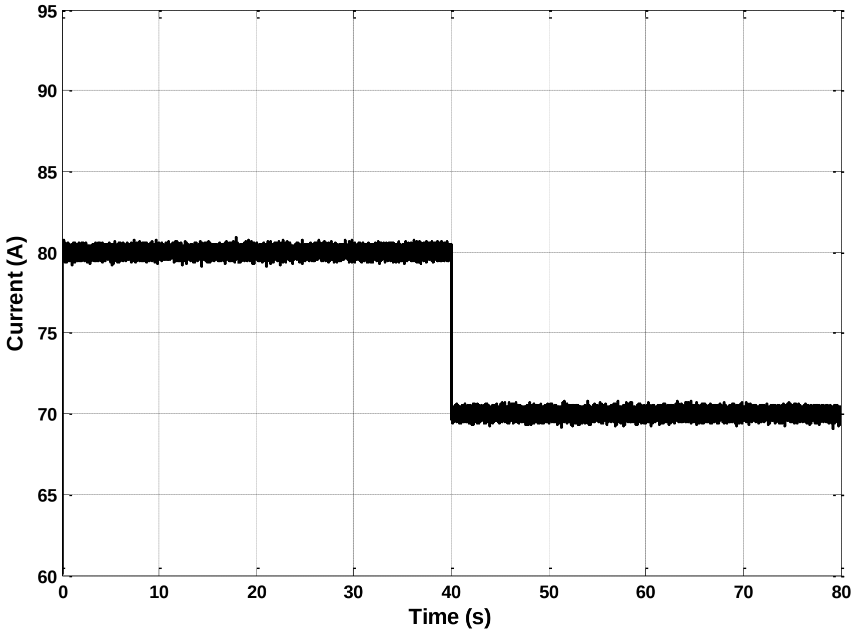

Figure 8. Variations of noisy load current

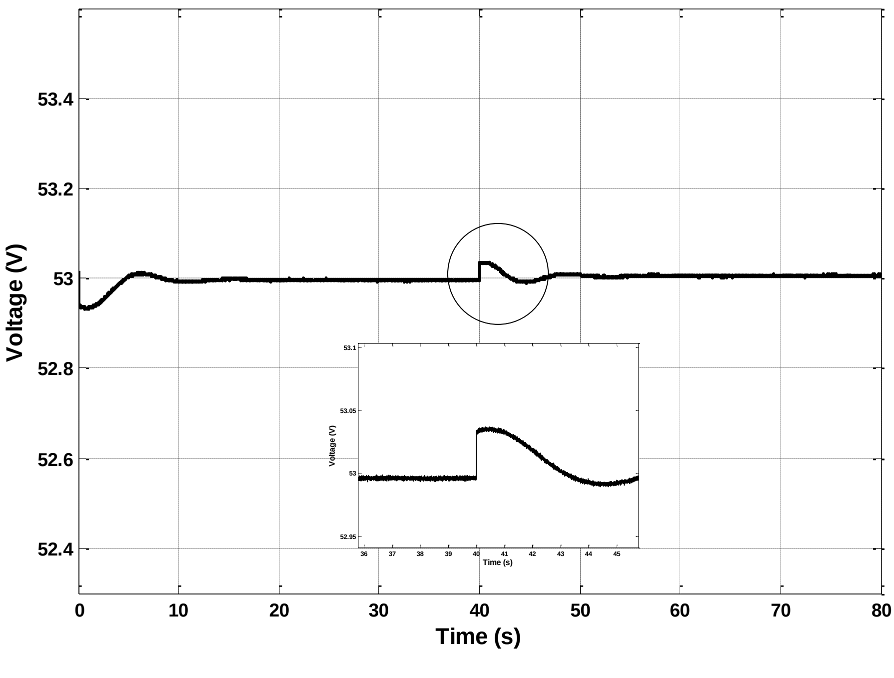

Figure 9. Performance of controller against added noise to the load current

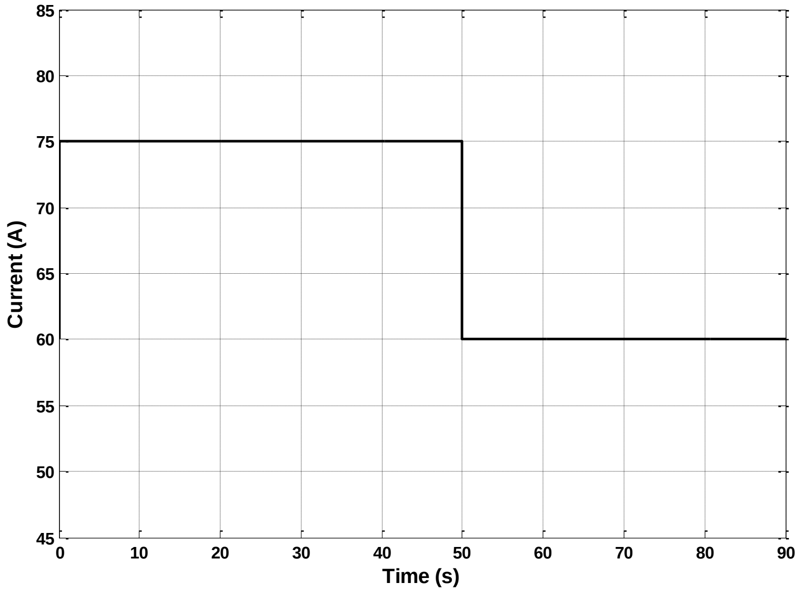

Figure 10. Curve of applied load current

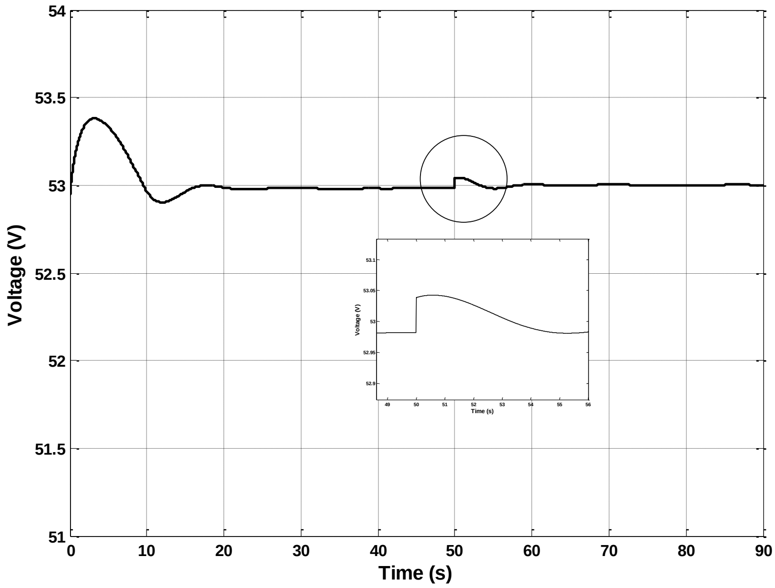

Figure 11. Performance of controller against added noise to output voltage

6. CONCLUSION

In this investigation, we proposed a RBF-based adaptive inverse control strategy for voltage control of PEMFC system. The used approach, based on combination of RBF network and a PD controller, satisfied the control objective with high degree of accuracy. The robustness of control scheme is also investigated and satisfactory performance of controller was observed.

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