

Modeling and Control of Fuel Cell Using Artificial Neural Networks

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ABSTRACT

This paper includes an experimental study of hydrogen mass flow rate and inlet hydrogen pressure effect on the fuel cell performance. Depending on the experimental results, a model of fuel cell based on artificial neural networks is proposed. A back propagation learning rule with the log-sigmoid activation function is adopted to construct neural networks model. Experimental data resulting from 36 fuel cell tests are used as a learning data. The hydrogen mass flow rate, applied load and inlet hydrogen pressure are inputs to fuel cell model, while the current and voltage are outputs. Proposed model could successfully predict the fuel cell performance in good agreement with actual data. This work is extended to developed fuel cell feedback control system using PID controller to stabilize the fuel cell voltage. Particle swarm optimization technique is used to tune the PID controller respectively. Simulation results showed that using PID controller with proposed model of fuel cell can successfully improve system performance in tracking output voltage under different operating conditions.

Key words: fuel cell, hydrogen fuel, renewable energy, artificial neural networks, PID, Particle swarm optimization

النمذجة والسيطرة لخلية وقود باستخدام الشبكات العصبية الاصطناعية

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الخلاصة

تتضمن هذه الورقة دراسة عملية لتأثير معدل كتلة تدفق الهيدروجين و ضغطه على أداء خلية الوقود. بالاعتماد على النتائج التجريبية، تم اقتراح نموذجا لخلية الوقود مبنيةعلى أساس الشبكات العصبية الاصطناعية. طريقة الانتشار الخلفي مع دالة التفعيل من النوع (log-sigmoid) اعتمدت لانشاء نموذج الشبكة العصبية. استخدمت البيانات التجريبية الناتجة من 36 اختبار لخلية الوقود كبيانات للتعلم. معدل تدفق كتلة الهيدروجين و الحمل المطبق و ضغط الهيدروجين اخذت كمدخلات لنموذج التلية، في حين أن التيار الكهربائي والجهد الكهربائي اصبحت المخرجات. النموذج المقترح تمكن من التنبئ بنجاح بأداء خلية الوقود مع حصول توافق جيد مع البيانات الفعلية. هذا العمل تم توسيعه ليشمل تطوير نظام سيطرة لخلية الوقود باستخدام المتحكم التناسبي التفاضلي التكاملي لتحقيق الاستقرار في جهد الخلية . استخدمت تقنية أمثلية حشد الجسيمات لحساب المتحكم على التوالي للمسيطر التناسبي التكاملي التفاضلي. الخط الجهد ومعدل تدفق الهيدروجين هما الادخال و المشخل المتحكم على التوالي للموريا ي المحاكاة أن استقرار في جهد الخلية . استخدمت تقنية أمثلية حشد الحساب المتحكم على التوالي المعمريا التكاملي التفاضلي. الخطأ الجهد ومعدل تدفق الهيدروجين هما الادخال و المشخل المتحكم على التوالي لمورة التاسبي التكاملي التفاضلي. الخطأ الماس ومعدل تدفق الهيدروجين هما الادخال و المشعل المتحكم على التوالي . أظهرت نتائج المحاكاة أن استخدام جهاز تحكم مع النموذج المقترح لخلية الوقود امت المشال المناحمة المتحال في المشخل المتحكم على التوالي . أظهرت نتائج المحاكاة أن استخدام جهاز تحكم مع النموذج المقترح لخلية الوقود امكنه تحسين أداء



1. INTRODUCTION

The fuel cell is a device that converts chemical energy into electrical energy and is more efficient than the internal combustion engine in fuel conversion to twice or three times the energy ,Ferng et al. 2004. The electrochemical cell uses to produce electrical energy continuously through the supply of oxygen and hydrogen ,Kordesch, 1996. For a hydrogen/oxygen fuel cell the inputs are hydrogen (fuel) and oxygen (oxidant) and the outputs are dc power, heat, and water. In general, the hydrogen is oxidized to protons moving through the electrolyte to the anode, as well as to electrons moving from outside the cell to the anode where they will meet with oxygen is reduced to water takeaways. There are various types of fuel cells developed and used over the years and can be classified either as types of fuel and oxidizer or as electrolyte type or working temperature of the cell or by mechanism of reactants entry to the cell, but the most common type of classification common is the classification cell according to the type of electrolyte used. These types of fuel cells could produce electrical power ranging from mille watts to megawatts. It could be used in a structure of portable electronic equipment, vehicles, residential or in distributed power systems ,Mann, 2004.When pure hydrogen is utilized no pollutants are produced, and the hydrogen itself could be generate from water using renewable energy sources such that the system is environmentally benign. Practically hydrogen was the best fuel for most applications. In addition to hydrogen several fuel cells could also use carbon monoxide and natural gas as a fuel. In these fuel cells, carbon monoxide reacts with water generating hydrogen and carbon dioxide, and natural gas reacts with water producing hydrogen and carbon monoxide, the hydrogen that generated is then used as the actual fuel.

For the purpose of study and improve the performance of fuel cell, many different mathematical models were proposed to speculation the behavior of voltage change with discharge current of a fuel cell. Recently, theoretical modeling and programming simulation have been developed for understanding better the fuel cell itself. Artificial neural network model has been provided useful and reasonably accurate input–output relations because of its excellent multi-dimensional mapping capability.

The neural networks architectures have been used for power analysis of fuel cell are multilayer feed forward network, radial biased function network, generalized regression neural network and adaptive neuro fuzzy interface systems ,**Mohanraj**, 2015.

K. Mammar et al. applied artificial neural networks for creating the optimal model of proton exchange membrane (PEM) fuel cell. The ANN network had an input layer with three inputs: partial pressures of hydrogen, partial of oxygen and cell operating current, one hidden layer with 10 neurons and an output layer with one outputs of fuel cell voltage. They create fuzzy logic controllers to control active power of proton exchange membrane fuel cell (PEMFC). Their results assured the high performance capability of the neural network to control power generation.

B. Grondin et al., Mammar, 2012. have been used A mechanistic and an artificial neural network (ANN) model to depict all internal phenomena in a single-cell for PEM fuel cell .They illuminate the benefits and drawbacks of the two different models using statistical error criteria. In S. Rakhtala et al. ,Grondin,2014. work, a neural network model was used as control algorithm of the fuel cell voltage to improve fuel cell performance. Air pressure was the control signal applied to the system and fuel cell voltage was the output .The system behavior has been tested under random current variations and compared to the fuel cell nonlinear dynamic model. J. Zamora1 et al. Rakhtala, 2011. presented the modeling of a PEM fuel cell system, by ANNs. The selected ANN structure was validated for the transient state, during the start up of the

system, and in steady state. The training strategy and the ANN topology were tested with a large number of parameters and network structures, to obtain high precision results.

The primary purpose of this research is to build a model for fuel cell using neural networks. The objective of this model is to estimate fuel cell power depend on training data: hydrogen mass flow rate, hydrogen pressure, applied load, current and voltage. The training data are collected from real tests measurements.

The automatic control of the fuel cell is very important case to improve the performance of it. The present work is widened to investigate the performance of the fuel cell control system using neural networks model and PID controller.

The proportional integral derivative (PID) controller is widely used in the industry because of its simple structure and robust performance within a wide range of operating conditions ,**C.Kao**, **2006**. Unfortunately, it has been difficult to correctly adjust the gains of PID controllers because many industrial systems have complex physics phenomena such as: high orders; time delays; and nonlinearities.

In this paper a particle swarm optimization (PSO) technique is used to tune the parameters of the PID controller for fuel cell.

2. FUEL CELL PERFORMANCE

2.1 Electrochemistry

In a fuel cell, there is no combustion processes because reaction takes place between fuel and oxygen at low temperature and the products of reaction were electric current, heat and water. Furthermore, they are environmentally friendly ,**Parsons**, **2000**.

In PEMFC type fuel cell, hydrogen flow over the anode pole where it was decomposed into electrons and protons (hydrogen ions). The hydrogen ions pass through the polymer electrolyte membrane which considers the center of the cell **,Larminie, 2012**. Then with the oxygen at the cathode, the hydrogen ion reacts with oxygen to generate water. Electrons created at the anode cannot pass through the membrane; therefore they flow through an external electric circuit from the anode to the cathode. In fact, the electrochemical reactions and the physical procedures, which occur at the cell poles, are very complex reactions. At the anode, hydrogen gas must spread through the winding paths to meet the platinum particles, where the platinum dismantle molecule of hydrogen to two atoms of hydrogen (H) and only then can the hydrogen atom to disintegrate into a proton and an electron through the outer circuit. This process is going through several stages before it reaches its end .In fact, platinum is the only currently known catalyst capable of shorthand to conduct this reaction at low temperature. **Fig1.** represent a diagram illustrating the structure and operation of PEMFC type fuel cell,

2.2 Efficiency

The important parameter has been used to measure energy conversion in fuel cells is fuel cell efficiency which represents the ratio between the actual voltage produced in the fuel cell to the maximum ideal voltage of fuel cell ,**Kordesch**, **1996**.

The calculation of ideal voltage which could be produced from fuel cell can be made by carrying out the process of energy balance between the initial state of the reactions in the chemical $\begin{pmatrix} 1 \\ 1 \end{pmatrix}$

reaction in the cell $\left(H_2 + \frac{1}{2}O_2\right)$ and the final state of reaction product H₂O.

The balance process has been representing by a Gibbs free energy. The maximum ideal voltage of the cell (ΔE) at constant pressure and temperature is **,Kordesch, 1996**.



$$\Delta E = \Delta G / nf \tag{1}$$

$$\Delta G = \Delta H - T\Delta S \tag{2}$$

where:

 ΔG is the deference in Gibbs free energy n is the number of moles of electrons f is Faraday constant ΔH is the deference in enthalpy

T is the cell temperature

 ΔS is the deference in entropy

The thermal efficiency of fuel cells can be representing as the ratio between the useful electrical energy to the heat that is generated from fuel, that is, enthalpy of formation. Therefore, the fuel cell maximum efficiency in the ideal state can be defined as the ratio between Gibbs free energy to the enthalpy of formation, that is,

Efficiency =
$$\frac{\Delta G}{\Delta H}$$
 (3)

The generated voltage is less than ideal voltage because of irreversible losses. There are three types of irreversible losses which working on reduce the performance of the cell. These losses are activation polarization, Ohmicpolarization, and concentration polarization ,Mann, 2000 and Larminie, 2000.

There are several types of fuel cells which were developed and used during the last few years. They are classified depending on the type of fuel and oxidant or type of electrolyte or cell operation temperature or the reactants entering method to the cell, however, the common classification is that of type of electrolyte used in the cell. The proton exchange membrane fuel cell (PEMFC) is the most used for many reasons, the most important reason is it operates at relatively medium temperature and the solid membrane it uses. Those reasons make this type of fuel cells appropriate for various applications, especially in cars and other means of transport, mobiles, computers and household appliances. The most important advantages are high energy density and fast startup as well as simple structure and safety in operation fuel cell **,Youssef, 2010.**

3. EXPERIMENTAL SETUP

The fuel cell unit is supplied with a stack of proton exchange membrane fuel cell (PEMFC) with a rated power of 100 W. The stack is composed of 24 cells with the shape of channeled plate that allows the air flow through the membrane. The membrane facilitates the hydrogen flow, generating the electrons release. There are separating plates which conduct electricity, allowing thus such electrons flow, between each pair of cell. The schematic of the experimental setup and a photograph of the fuel cell unit are shown in **Fig 2**.

Cells are self- humidifying and do not require any type of external humidification. The stack has an integrated fan able to provide the required air for the good operation and maintenance of the operation temperature. Hydrogen storage represents one of the essential points regarding the hydrogen economy. For that purpose, a canister of metal hydride (300L) is included. Internal pressure of the device is 8 bar at a room temperature of $20-25^{\circ}$ C. It has discharge pressure of 15-20 bar, for that reason the fuel cell unite also includes two pressure regulators. One of them is for it's the installation in the H2 cylinder in order to regulator the outlet pressure at 30 bar. The other is placed at the outlet of the metal hydride canister in order to regulate the inlet pressure to the stack in a range of 0.4 - 0.5 bar. In additional, the unit includes two solenoid valves. One of them is located before the stack. It controls the hydrogen inlet and when the unit is switched off, the valve is closed to avoid any possible hydrogen leakage. This valve is automatically closed when the temperature of the stack exceeds 65 °C. The other valve is placed at the stack outlet. It purges outside the excess of water and hydrogen for a correct operation.

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The unit also has load regulation system. It enables the study of the generated electrical energy, the representation of the characteristic operation curves and their comparison with theoretical curve. It included a variable power, which enables to vary the generated current.

The whole electrical circuit of the stack is protected by a short circuit unit in case over current (12A) and low voltage shut down (12V). In the event of one of these problems, the hydrogen inlet solenoid valve is automatically closed.

Lastly, and as a result of the danger in the use of hydrogen, include a hydrogen leak detector with a detection range from 0 to 2% Vol.

4. EXPERIMENTAL RESULTS

Figures (3), (4) and (5) show the effect of hydrogen flow rate and inlet pressure on fuel cell performance parameters. The current density-voltage relationship for a fuel cell and operating conditions (concentration, flow rate, pressure, temperature, and relative humidity) is a function of kinetic (activation), ohmic, and mass transfer resistances. The current density vs. voltage curve, shown in figure 3 at different inlet pressure, the figure is called as the polarization curve. Deviations between the ideal equilibrium voltage and the polarization curve provide a measure of fuel cell efficiency. These results give a good agreement with published results , Ferng, 2004, Rowe , 2001.

Electrical energy is gained from a fuel cell when a current is drawn, but the actual cell voltage has been lowered from its equilibrium voltage because of irreversible losses due to several reasons. Several factors give the irreversible losses in a practical fuel cell. The losses, which were generally called polarization, formed primarily from activation polarization, ohmic polarization, and gas concentration polarization. The activation loss is the first of these polarizations, Performance loss due to slow reaction kinetics at either/both the cathode and anode surfaces is called activation polarization. Activation polarization is related to the activation energy barrier between reacting species and it is primarily a function of temperature, pressure, concentration, and electrode properties. The reactions can also play a role in activation polarization. Kinetic resistance rules the low current density portion of the polarization curve, where deviations from equilibrium were small. At these conditions, reactants were plentiful (no mass transfer limitations) and the current was so small that ohmic (iR) losses were negligible.

Performance loss resulting from resistance to the flow of current in the electrolyte and through the electrodes is called ohmic polarization, the ohmic polarization change with the current increase. Ohmic polarization is present using Ohm's Law (V=iR), where i is current density (mA/cm^2) and R is resistance (W-cm²), and command in the linear part of the current density-voltage curve as shown in figure 4. The concentration losses happen significantly at all range of current density [Chou, 2003].

Concentration polarization has been happen when a reactant is interacting on the surface of the electrode cause a concentration gradient between the gas and the surface. Concentration polarization has been affected by concentration and flow rate of the reactants, the temperature of fuel cell temperature, and the structure of the gas diffusion layer and catalyst properties ,**Mann**, **2000.**

Numbers of processes have been caused the formation of the concentration polarization. These are (1) diffusion difficulties of the gas phase in the electrode pores, (2) solution formation of reactants into the electrolyte, (3) dissolution formation of products out of the system ,**Chou**, **2003.**

In **Fig 3.** it can be seen that the increase of operating inlet pressure leads to decrease of losses, which mean high voltage output. An increase in operating pressure has several positive effects on fuel cell performance. The partial pressures of reactant gases, solubility, and mass transfer rates are higher at higher pressures. The electrolyte loss by evaporation is reduced at higher operating pressures. The system efficiency is increased by the increase in pressure.

This is evident from **Fig4.** where can be observed decrease cell efficiency with the increase in operating pressure. As can be observed decrease in efficiency with increasing hydrogen flow rate so that the maximum efficiency of the cell was at low current densities and high voltage due to increased losses with increasing current density as described in **Fig4.** In fact, as the current density is decreased, the active cell area must be increased to obtain the desired amount of power.

The variation of power with current density is shown in **Fig5.** Where power increased with current density increase, it is normal and seems logical to design the cell to operate at the maximum power that peaks at a higher current density. However, operation at the higher power will mean operation at lower cell voltages or lower cell efficiency. Setting the operating point at the peak power density may cause instability in power control because the system will have a tendency to oscillate between higher and lower current densities around the peak. It is normal practice to operate the cell at a point towards the left side of the power peak and at a point that yields a compromise between low operating cost (low current density) and low capital cost (high current density).

4. Fuel cell modeling

A fully connected feed forward multi-layer configuration using back propagation learning algorithm was implemented to model the fuel cell. This type of ANN has a strong ability to express complex non-linear mapping and has already found wide ranging applications ,**Khandekar**, 2002.



The structure of this type of ANN usually consists of an input layer, hidden layer (one or more) and an output layer. Each layer has some nodes representing artificial neurons. Each node connected to the nodes of its preceding layer through adaptable weights ,Latha, 2010. Individual neurons have limited ability of calculation and expression but when they connect with each other, the whole network achieves ability to model complex functions. A network accepts an input vector and generates a response in the form of an output vector as shown in Fig6.

The concept of learning of neural networks related to finding the values of weights such that the error condition was minimized. The error is the difference between the actual output vector to the estimated output vector by neural networks and the resulting error back propagates to alter the connecting weights in the direction of reducing the error. This process does running many times until the error reaches to the lowest possible value. Then the network holds the weights constant and becomes a valid model for prediction. **Latha**, **2010**.

In this work, the pressure, mass flow rate and generated power are considered as inputs to the network. The current and voltage are network output. In present work, ten nodes in hidden layer are adopted. Mean squared error concept has been used to express about the error incurred during the learning as shown in equation (4)

$$Error = \frac{1}{2} \sum_{1}^{m} (V_{act} - V_{est})^2 + (I_{act} - I_{est})^2$$
(4)

where *m* is the number of patterns V_{act} is actual voltage, V_{est} is estimated voltage by neural networks model, I_{act} is actual current, and I_{est} is estimated current by neural networks model. The algorithm of the neural networks for fuel cell model is carried out using MATLAB version 2012.

A training set of 36 patterns is used with a learning rate of 0.1. After 12 epochs, the output of the neural network is approximated to the actual output (voltage and current) as shown in figure (7). The error is equal to $7.4 e^{-6}$ for excellent learning of fuel cell model as shown in **Fig8**.

5. PID CONTROLLER

The presented PID Controller in this work has been consisted of classic PID controller, direct closed-loop control of controlled objects and particle swarm optimization (PSO) technique to find PID controller parameters k_p , k_i ; and k_d to reach optimization of control performance index according to system operating condition as shown in **Fig9.** The plant is fuel cell model based on neural network which is described in previous section.

In PSO algorithm, the system has been initialized with particles of random solutions, which, and each potential solution has been also assigned a randomized velocity. Each particle adjusts its trajectory towards its best solution (fitness) that is achieved so far. This value is called *pbest*. Each particle also modifies its trajectory towards the best previous position attained by any member of its neighborhood. This value is called *gbest*. Each particle moves in the search space with an adaptive velocity.

The particles have been evaluated using a fitness function to see how close they are to the optimal solution.

$$V_{i,n}^{m+1} = V_{i,n}^{m} + c_1 rand_1 (pbest_{i,n}^{m} - x_{i,n}^{m}) + c_2 rand_2 (gbest_n^{m} - x_{i,n}^{m})$$
(5)



$$x_{i,n}^{m+1} = x_{i,n}^m + V_{i,n}^{m+1}$$
(6)

where

 $V_{i,n}^{m}$ is the velocity of the *i*th particle at *m*th iteration.

 $X_{i,n}^{m}$ is the position of the *i*th particle at *m*th iteration.

I is number of particles.

n is the dimension of particle.

 c_1 and c_2 are the acceleration constants with positive values equal to 1.17.

 $rand_1$ and $rand_2$ are random numbers between 0 and 1.

pbest, is best previous weight of ith particle.

gbest, is best particle among all the particle in the population.

In present analysis, $\Delta K_n^{m+1} = V_{i,n}^{m+1}$, $\Delta K_n^m = V_{i,n}^m$ and $K_n^m = x_{i,n}^m$, where K are the parameters K_n K and K of the PID controller. The mean square error function is chosen as criterion for

 K_p , K_i and K_d of the PID controller. The mean square error function is chosen as criterion for estimating the model performance as equation (7)

$$E = \frac{1}{p} \sum_{j=1}^{p} (V_{ref} (m+1)^{j} - V_{out} (m+1)^{j})^{2}$$
(7)

where p is number of samples, V_{ref} is desired voltage and V_{out} is fuel cell output voltage.

6. Simulations Results

In this section, the performance of proposed fuel cell model with PID which its parameters have been tuned by PSO is tested .The task of present controller assumes the fuel cell must give desired voltage when the load has been applied on it. This means the time history responses of fuel cell voltage under different working condition have been tested using suggested PID controller as shown in **Fig10**. It can be seen from this figure, the suggested PID controller is able to make the fuel cell gives the desired voltage (18 volt) at short time not exceed 1sec depending on the operating pressure and load. The pressure changes 0.4, 0.45 and 0.5 bar , while the load (power) is applied at values of 50,80,and 100 W. The responses seem smoothly and without over shoot. These results show the voltage output reaches the desired value quickly as applied power decreases.

Fig 11. show the time history responses of hydrogen mass flow rate. it can be seen from this figure, the controller give more mass flow when the pressure decreases .Also, when the applied load increases from 50 to 100 W the mass increases by 29% ,42% and 73% at pressure 0.4,0.45 and 0.5 bar respectively.

7. CONCLUSIONS

The performance of the fuel cell is studied experimentally. The experimental results appear that the polarization curve is identical with the theoretical polarization curve of fuel cell where the three types of losses are clear and showed the same behavior known of the cell. The hydrogen inlet pressure increased has a significant effect on the performance of fuel cell where the losses are decreased when the inlet pressure increase. The fuel cell efficiency decrease with the increase the operating pressure and hydrogen flow rate. The maximum efficiency of the cell was at low current densities and high voltage. The operating point the fuel cell must be selected so that the power output greater as possible, taking into consideration both of the cell voltage and efficiency were their being inversely proportionate with the power output.

A fuel cell model based on artificial neural networks with back propagation algorithm is successfully trained, validated and used for prediction the performance of fuel cell under different working conditions. The using of neural networks to model complicated physical systems is very good choice because it deals with the input –output data of the systems regardless of the composition source.

Also, in this paper, PID controller with PSO technique for tuning its gains is used to control output voltage of fuel cell under different pressure and applied load. Present controller can offer good performance with fast response and without overshoot. This response reflects the fuel cell speed access to the required operating conditions, and this feature is one of the most important features that are characterized by fuel cells for mechanical engines.

Finally, the increase in pressure may decrease the controller power and the Consumption of hydrogen.

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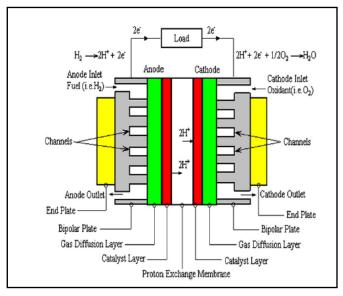
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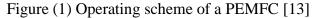


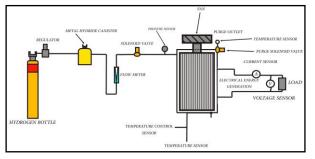
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(a)





Figure 2. Schematic diagram and photograph of fuel cell experimental setup.



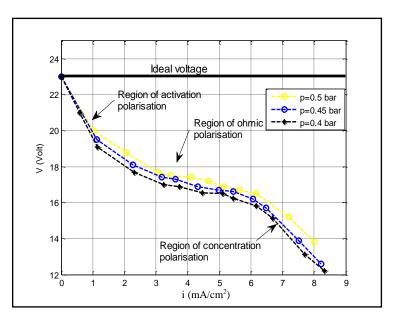
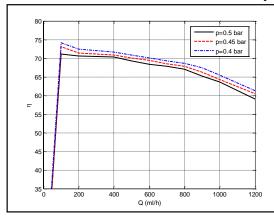


Figure 3. Experimental results of the polarization curve at different inlet hydrogen pressure



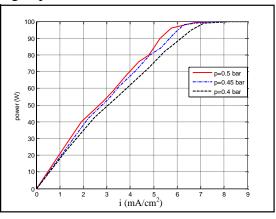


Figure (4) Variation of fuel cell efficiency with hydrogen flow rate at different inlet hydrogen pressure

Figure (5) Output power relation with current density at different inlet hydrogen pressure

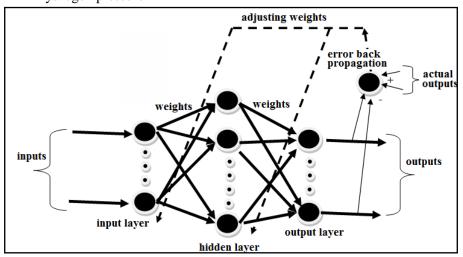


Figure 6. Neural networks structure



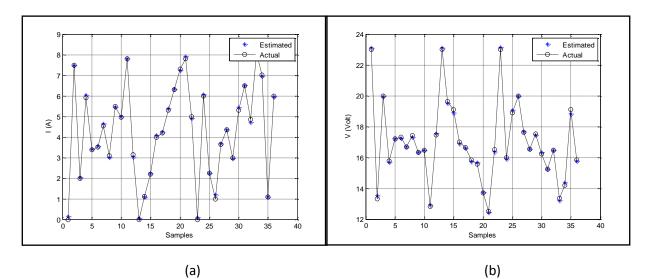


Figure 7.Current and voltage; estimated by neural networks model vs. actual data

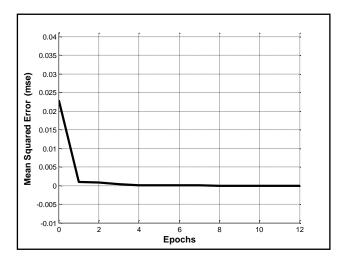


Figure 8. Mean square error vs. epoch

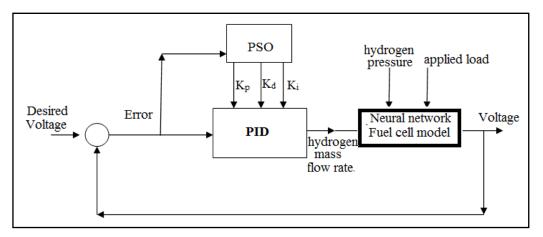
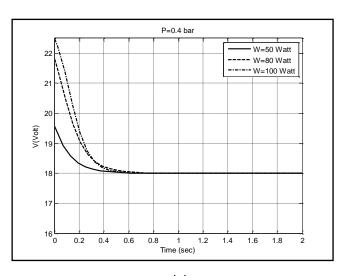
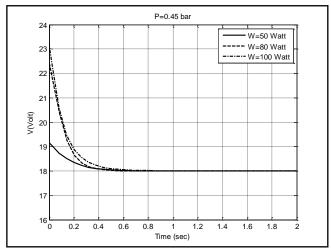
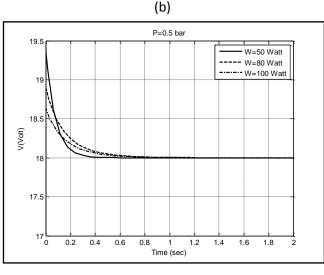


Figure (9) PID controller structure









(c)

Figure 10. Time history response of voltage output of fuel cell at different operating conditions

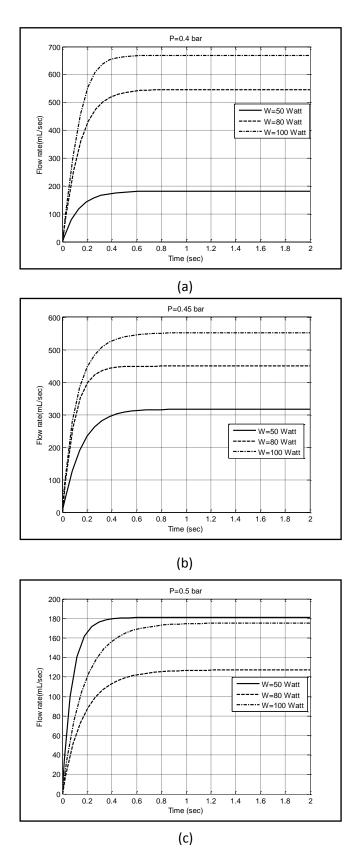


Figure 11.Time history response of hydrogen flow rate of fuel cell at different operating conditions