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An Efficient Fuel Cell Maximum Power Point Tracker based on an Adaptive Neural Fuzzy Inference System

Abstract *In this article, we develop a Maximum Power Point Tracker (MPPT) for a fuel cell system based on an Adaptive Neural Fuzzy Inference System (ANFIS). The system considered consists of a Proton Exchange Membrane fuel cell (PEMFC) connected to a resistive load via a boost converter, an ANFIS giving the reference signals (the voltage and the current values of the maximum power point whatever the operating conditions of the fuel cell), and a PI (Proportional integrator) controller with a Pulse Width Modulation (PWM) signal generator to tuning the duty cycle of the DC-DC boost converter. The ANFIS training database uses samples calculated using a validate fuel cell electrochemical model. The simulation results obtained using Matlab-Simulink package demonstrate the effectiveness of the proposed MPPT compared to conventional MPPT techniques in terms of static and dynamic performance.*

Streszczenie. *W tym artykule opracowujemy śledzenie punktu maksymalnej mocy (MPPT) dla systemu ogniw paliwowych opartego na Adaptive Neural Fuzzy Inference System (ANFIS). Rozważany system składa się z ogniwa paliwowego z membraną do wymiany protonów (PEMFC) połączonego z obciążeniem rezystancyjnym poprzez konwerter doładowania, ANFIS dający sygnały odniesienia (napięcie i wartości prądu maksymalnego punktu mocy, niezależnie od warunków pracy ogniwa paliwowego) oraz sterownik PI (proporcjonalny integrator) z generatorem sygnału z modulacją szerokości impulsu (PWM) do dostrajania cyklu pracy przetwornicy podwyższającej DC-DC. Baza danych szkoleniowych ANFIS wykorzystuje próbki obliczone przy użyciu walidacyjnego modelu elektrochemicznego ogniw paliwowych. Wyniki symulacji uzyskane przy użyciu pakietu MATLAB-Simulink pokazują skuteczność proponowanego MPPT w porównaniu z konwencjonalnymi technikami MPPT pod względem wydajności statycznej i dynamicznej. (**Wydajny moduł śledzenia maksymalnego punktu mocy ogniwa paliwowego oparty na adaptacyjnym systemie wnioskowania neuronowego Fuzzy**)*

Keywords: Adaptive Neural Fuzzy Inference System (ANFIS), Proton exchange membrane fuel cell (PEMFC), Maximum power point tracking (MPPT)
Słowa kluczowe: Adaptacyjny Neural Fuzzy Inference System (ANFIS), Ogniwo paliwowe z membraną do wymiany protonów (PEMFC), Śledzenie punktu maksymalnej mocy (MPPT)

Introduction

Currently countries mainly rely on coal, oil and natural gas for their energy supply [1, 2]. These fossil fuels are not renewable, namely they depend limited resources that will certainly decrease, and becoming too expensive in addition to their damage of the environment [1, 3]. Among the technologies expected to replace fossil fuels, fuel cells (the only converter of hydrogen into electricity) have the potential to provide the world with clean and sustainable electrical energy [2]. Fuel cell offer many advantages. It's efficient, reliable, quiet, and it emit no greenhouse gases [4].

Fuel cell technologies are generally categorized according to their electrolyte and operating temperature. A PEMFC operates with a polymer electrolyte and its operating temperature is about 80 °C [5]. Due to its characteristics such as fast start-up, light weight, high power density and low operating temperature, PEMFC is the most popular type of fuel cell and the best candidate for residential and vehicular applications [4, 5].

The current-voltage characteristic of fuel cells is non-linear and is influenced by operating parameters such as temperature, oxygen partial pressure, hydrogen partial pressure and membrane water content [6, 7]. At particular operating conditions, there is a single operating point where the power delivered by the fuel cell is at its maximum. Therefore, it is important to find this maximum power point (MPP) defined by its voltage (V_{mpp}) and current (I_{mpp}) in order to increase the efficiency of the system. This approach is referred to as the maximum power point tracking. A MPPT (Maximum Power Point Tracker) is a DC-DC converter controlled to enforce the fuel cell to operate at its maximum power point [7, 8]. MPPT techniques constitute a wide field of research with the aim of improving the efficiency of renewable energy systems [8-12]. The diversity of these methods is basically developed for photovoltaic systems [13]. The best known methods are the "perturb and observe" method and the "incremental conductance" method due to their simplicity and low cost [14]. However, their drawbacks (fluctuation around the maximum power point and tracking error in case of fast operating conditions change) have led to propose alternative algorithms based on artificial intelligence techniques [15-19].

This paper presents a MPPT suitable for a PEMFC system based on an ANFIS and a DC/DC boost converter. ANFIS systems don't need to know the fuel cell system internal parameters, use less electrical sensors and less computing resources.

Fuel cell model

Fuel cells are efficient electric power generating systems that convert the chemical energy of hydrogen directly into electrical energy and heat [20]. The operating principle of a PEMFC requires an elementary cell comprising an anode, a cathode, an electrolyte as well oxygen and hydrogen supply systems (Fig. 1) [21].

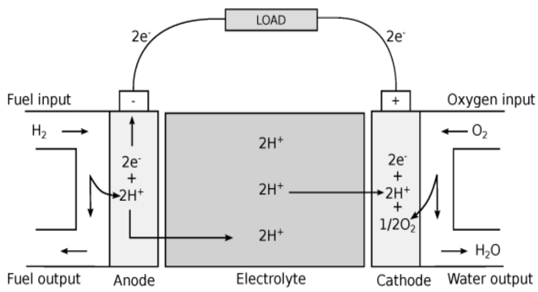

Fig.1. Fuel cell principle [4]

At the anode occurs the catalytic oxidation of hydrogen which comes apart from its electrons:

$$H_2 \rightarrow 2H^+ + 2e^-$$

At the cathode occurs the catalytic reduction of oxygen, producing heat and water:

$$O_2 + 4H^+ + 4e^- \rightarrow H_2O$$

The overall reaction is therefore:

$H_2 + 1/2O_2 \rightarrow H_2O$ + heat + electricity

By physically separating the anode and the cathode reactions using an electrolyte, the electrons released by the oxidation of hydrogen pass through the external electrical circuit forming a direct electrical current while the H^+ ions formed can pass through the electrolyte.

R. F. Mann et al. [22] developed an electrochemical based fuel cell model which gives the fuel cell voltage as a function of its current taking into account the essential electrochemical phenomena that take place inside it.

The expression of the voltage of a single fuel cell is expressed as follows:

(1) $$E_{Cell} = E_{Nernst} - E_{act} - E_{ohm} - E_{con}$$

where E_{Nernst} is the Nernst potential of the cell (V), E_{act} is the activation overvoltage (V), E_{ohm} is the ohmic overvoltage (V) and E_{con} is the concentration overvoltage (V).

The voltage E_{Stack} (V) of a stack formed by n cells connected in series is:

(2) $$E_{Stack} = n.E_{Cell}$$

The Nernst voltage of a single fuel cell under normal pressure and temperature conditions is around 1.229 V. The following formula calculates the Nernst voltage for any conditions of temperature and pressure:

(3) $$E_{Nernst} = 1{,}229 - 0{,}85T^{-3}.(T - 298{,}15) + 4{,}31.10^{-5}.T.\left[ln\left(P_{H_2}\right) + \frac{1}{2}ln\left(P_{O_2}\right)\right]$$

where T is the absolute operating temperature of the stack (K), P_{H_2} is the hydrogen partial pressures (atm) and P_{O_2} is the oxygen partial pressures (atm) [21, 22].

Activation over-voltage is given by the relation:

(4) $$E_{act} = \xi_1 + \xi_2.T\xi_3.T.ln\left(c_{O_2}\right) + \xi_4.T.ln(i_{FC})$$

where i_{FC} is the functional fuel cell operating electrical current (A). ξ, ξ_2, ξ_3, and ξ_4 are empirical coefficients. c_{O_2} is the concentration of dissolved oxygen in the interface of the cathode catalyst (mol/ cm^3), determined by:

(5) $$c_{O_2} = \frac{P_{O_2}}{5.08.10^6.e^{-\left(\frac{498}{T}\right)}}$$

The ohmic over-voltage is determined by:

(6) $$E_{ohm} = i_{FC}.(R_M + R_C)$$

where $\mathrm{R_M}$ is the equivalent proton-exchange membrane impedance (Ω) and $\mathrm{R_C}$ is the resistance between the electrodes and the proton-exchange membrane (Ω). $\mathrm{R_M}$ is calculated as the following relation:

(7) $$\mathrm{R_M} = \frac{\rho_M.L}{A}$$

where L is the membrane thickness (cm), A is the cell active area (cm2), and ρ_M is the specific membrane resistivity (Ω.cm) obtained by the following relation:

(8) $$\rho_M = \frac{181{,}6.\left[1+0{,}003.\left(\frac{i_{FC}}{A}\right)+0{,}062.\left(\frac{T}{303}\right)^2.\left(\frac{i_{FC}}{A}\right)^{2.5}\right]}{\left[\psi-0{,}634-3.\left(\frac{i_{FC}}{A}\right)\right].exp\left[4{,}18.\left(\frac{T-303}{T}\right)\right]}$$

where ψ is an adjustable parameter function of the membrane water content and stoichiometry relation of the anode gas. ψ may have a value order of 14 under 100% of relative humidity and up to 23 at oversaturated conditions [21].

The concentration over-voltage related to the kinetics of diffusion of gases through the electrodes is given by the relation:

(9) $$E_{con} = -B.ln\left(1 - \frac{J}{J_{max}}\right)$$

where B (V) is an empirical coefficient it depends on the type of fuel cell and its operation state , J is the actual current density of the cell (A/cm^2), and J_{max} is the maximum current density (A/ cm^2) [21].

Equation (1) represents the steady state electrical model of the fuel cell. An equivalent electrical circuit can be used to model the dynamic behavior of the fuel cell (Fig. 2) [23].

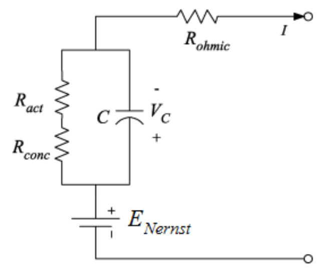

Fig.2. PEMFC Equivalent dynamic electrical circuit

In this circuit, ohmic over-voltage, activation over-voltage and concentration over-voltage are represented by the resistors R_{ohm}, R_{act} and R_{con} respectively, while the capacitor C models the delay of the activation and the concentration over-voltages in the case of change in fuel cell current. This delay is caused by the charge double layer in the electrode/electrolyte interface. For the 500-W BCS fuel cell stack, the value of this capacity is approximately 3 Farads [21].

Proposed Based MPPT ANFIS

An adaptive neural fuzzy inference system (ANFIS) combines the ability of neural networks to learn and the ability of fuzzy inference systems to use linguistic variables [24]. An ANFIS implements a Takagi-Sugeno fuzzy inference system of five hidden layers (Fig. 3). The first hidden layer is responsible for mapping the input variables relative to each membership function. The operator “AND” is applied in the second layer to calculate the truth value of each rule. The third hidden layer normalizes the truth value of the rule (weight). At the fourth hidden layer, the parameters called “rules consequents” are determined. The last layer delivers the ANFIS response defined by the sum of all the incoming signals. ANFIS uses a back propagation learning method for the parameters of the input membership functions and the mean square error method to determine the rules consequents [25, 26, 27].

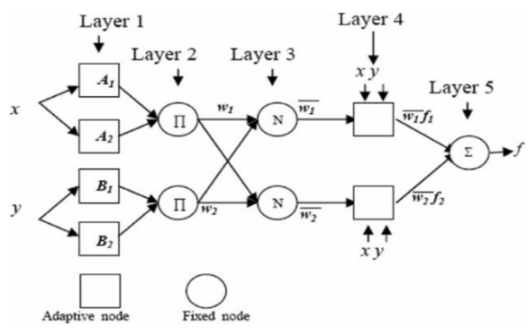

Fig.3. Basic ANFIS structure

The proposed ANFIS must be able to predict the voltage (V_{mpp}) and the current (I_{mpp}) of the maximum power point whatever the operating conditions of the fuel cell system. Fig. 4 shows the inputs and the outputs of the proposed ANFIS.

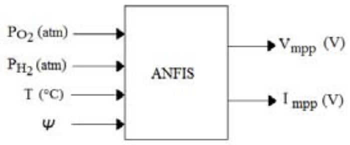

Fig. 4 Proposed ANFIS inputs/outputs

The input layer has four inputs: the partial pressure of hydrogen P_{H2} (atm), the partial pressure of oxygen P_{O2} (atm), the relative humidity factor of the membrane ψ and the operating temperature T (°C). The output layer has two outputs: the voltage (V_{mpp}) and the current (I_{mpp}) of the maximum power point. In practice, the input nodes are sensors delivering the measurements of the operating conditions of the fuel cell.

Simulation results

Fuel cell output characteristics

MATLAB® was used to perform simulation of the 500-W BCS PEMFC stack based on the fuel cell electrochemical model described above and simulation parameters presented on Table 1. Many articles in the literature present the electrical characteristics of this fuel cell stack [21, 28, 29]; which facilitates the validation of the simulation results.

Table 1 500-W BCS PEMFC simulation parameters [21]

Parameter	Value	Parameter	Value
n	32	ξ_1	-0.948
L	0.0178 cm	ξ_2	0.00312
B	0.016 V	ξ_3	$7.6.10^{-5}$
R_c	0.0003 Ω	ξ_4	$-1.93.10^{-4}$
A	64 cm^2	J_{max}	0.469 A/cm^2

Fig.5 shows the voltage-current curve and the power-current curve of the 500-W BCS PEMFC FC for standard conditions of pressure and temperature, and ψ equal to 14.

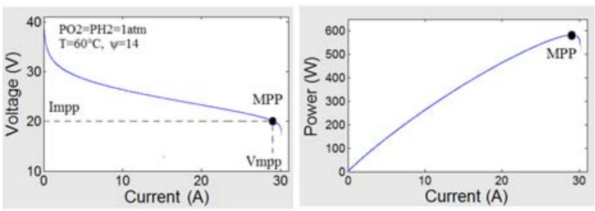

Fig. 5 500-W BCS stack electrical output characteristics

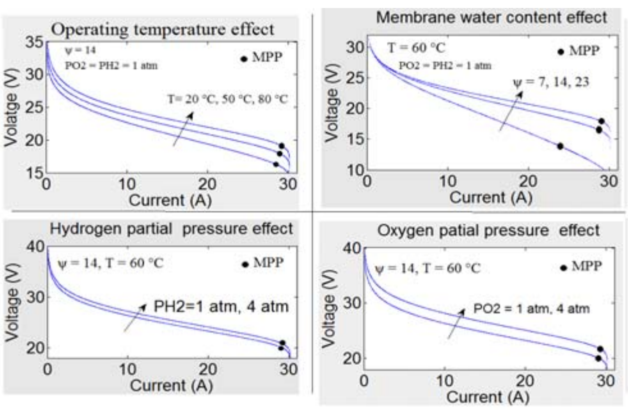

Fig. 6 Operating parameters effect on fuel cell polarization curve and maximum power point

A fuel cell is a non-linear DC power and there is always a single maximum point existing on the power curve at particular operating conditions. The output characteristics of a fuel cell are significantly affected by the operating parameters. The main factors are fuel cell temperature, hydrogen partial pressure, oxygen partial pressure and membrane water content. Fig. 6 shows the influence of each operating parameter on the current-voltage curve and the maximum power point.

It's clear that the maximum power point changes when operating conditions change. Therefore, to ensure that fuel cell output the maximum power even if operating conditions change rapidly, it is imperative to develop a highly efficient MPPT system.

ANFIS performances

The fuel cell electrochemical model is used to develop a set of maximum power points (V_{mpp} , I_{mpp}) for different fuel cell operating conditions serving as ANFIS training data samples (Table 2). One hundred twenty data were generated defined by operating conditions of the fuel cell and voltage and current values of the corresponding maximum power points.

Table 2 ANFIS training data sample

***T* (K)**	**P_{H2}=P_{O2} (atm)**	***Ψ***	**V_{mpp} (A)**	**I_{mpp} (V)**
298	1	7	13,93	23,80
298	1,5	7	14,23	24,20
298	2	7	14,50	24,40
. .	. .	. .	. .	. .
328	1	11	19,07	28,70
328	1,5	11	19,07	28,70
. .	. .	. .	. .	. .
358	4	23	22,26	29,40
358	4,5	23	22,45	29,40

During the training phase, the ANFIS parameters are adjusted so as to bring the current ANFIS output values very close to the target values. The learning is stopped when a level of precision defined beforehand by the mean square error value is reached. In our case, an acceptable precision is reached for a target mean square error fixed at 0.003.

The ANFIS was then tested for operating conditions different from those used during the training phase. The results are validated by comparing them to the values obtained using the fuel cell electrochemical model under the same operating conditions (Table 3)

Table 3 ANFIS accuracy

FC electrochemical model			**ANFIS**			**MP relative Error (%)**
V_{mpp} (V)	**I_{mpp} (A)**	**MP (W)**	**V_{mpp} (V)**	**I_{mpp} (A)**	**MP_{ANFIS} (W)**	
13.98	21.50	300.57	15.20	18.90	287.28	4.42
15.10	24.60	371.46	17.20	23.10	397.32	6.96
. .	. .	. .	. .	. .	. .	. .
18.60	28.50	530.10	20.10	25.50	512.55	3.31
22.49	29.30	658.96	24.50	28.10	688.45	4.48

Relative error of the maximum power (MP_{ANFIS}) predicted by the ANFIS compared to the maximum power calculated by the electrochemical model (MP) is calculated to assess the accuracy of the ANFIS. The maximum relative error value expressed in percentage is 7.52 % of the theoretical maximum power value. It seems that maximum power points predicted by the proposed ANFIS are very close to those obtained by the electrochemical model. This is confirmed by the linear regression curve (Fig.7) considering maximum power values calculated by the electrochemical model as inputs and the maximum power values predicted by the ANFIS as outputs.

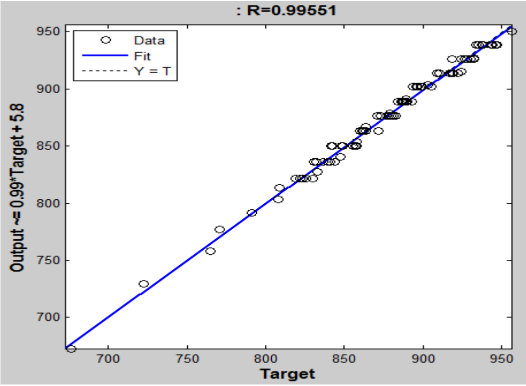

Fig. 7 Linear regression curve

Therefore, we can conclude that the developed ANFIS can accurately predict the fuel cell maximum power point for any fuel cell operating conditions.

DC-DC boost converter control

To illustrate the usefulness of the proposed ANFIS, it is used as an algorithm to provide the reference voltage for controlling the DC-DC boost converter connected to the fuel cell system (Fig. 8).

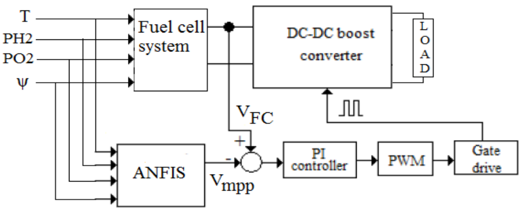

Fig. 8 Overall proposed MPPT system

The control is based on comparing the actual PEMFC voltage and the reference voltage given by the ANFIS block to continuously adjust the duty cycle of the DC-DC boost converter. For this, the error between the actual voltage and the reference voltage is introduced to a PI controller whose output is compared to a high frequency triangular signal to generate an appropriate PWM signal.

The system is tested in the case of rapid change in gases pressures, temperature and membrane relative humidity. A change in the operating conditions causes a change in reference voltage (and reference current) given by the ANFIS. Fig. 9 shows an example of voltage response in the case of a rapid change in fuel cell operating conditions.

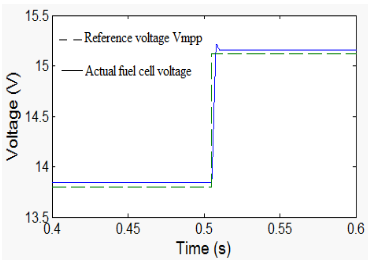

Fig. 9 Fuel cell voltage under varying operating conditions

The proposed MPPT exhibits a quick dynamic response with a very lower static error. Even in the event of fast operating conditions change, it finds accurately and quickly the new maximum power point. Compared to other published works [7, 30], the proposed ANFIS-based MPPT is characterized by fewer fluctuations around the maximum power point and rapid dynamic response.

Comparison among the proposed MPPT and the conventional “Perturb and Observe” MPPT technique

To assess the performance of the proposed MPPT, it is compared with the “Perturb and Observe (P&O)” MPPT technique. The “P&O” technique is by far the most widely used because of its simplicity.

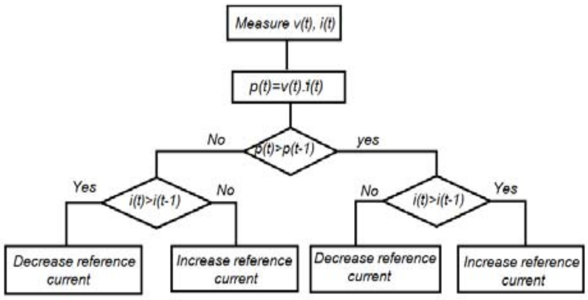

Fig. 10 Perturb and observe (P&O) MPPT algorithm

The basis algorithm of this technique is described in Fig.10. More details can be found in literature [31-34].

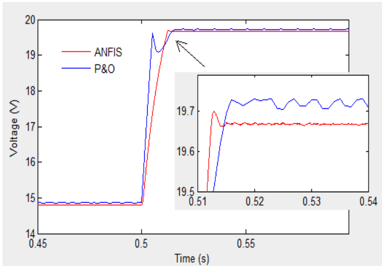

Fig. 11 ANFIS MPPT and (P&O) MPPT comparison

Fig. 11 shows the response of the ANFIS-based MPPT and the response of the P&O-based MPPT for similar changes in fuel cell operating conditions

The ANFIS-based MPPT exhibits improved dynamic response (steady state reached in a shorter time), and improved steady stat response (weaker fluctuations).

Conclusion

This article presents a synthesis of a maximum power point tracker based on an artificial neural fuzzy inference system (ANFIS) suitable for PEM fuel cell. The design and implementation of the proposed MPPT are performed using MATLAB software. A fuel cell electrochemical model was used to generate the database for the ANFIS learning as well as to validate the simulation results. The proposed MPPT ensure impedance matching between the load and the fuel cell for maximum power transfer by controlling the duty cycle of a DC–DC boost converter. Simulation results show that the proposed MPPT exhibits good static and dynamic performances whatever the fuel cell operating conditions compared to conventional MPPT. Comparison with the P&O technique confirms the ANFIS-based MPPT proposed for the fuel cell system is an effective methodology. However, the main drawback of the proposed ANFIS based MPPT is that it is exclusively suitable for the fuel cell stack for which it was developed. If another fuel cell stack is used, the ANFIS must be designed and trained again.

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