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A RBF artificial neural network to predict a fuel cell maximum power point

Abstract. *In this article, an artificial neural network (ANN) based maximum power point tracker (MPTT) for proton exchange membrane fuel cell (PEMFC) is proposed. For this purpose, a Radial Basis Function Artificial Neural Network (RBF ANN) is used to predict the voltage and the current of a fuel cell maximum power point at different fuel cell operating conditions. To train the proposed artificial neural network, a set of maximum power points defined by their corresponding current and voltage values is generated using a validated electrochemical fuel cell model. To ensure the validity of the ANN, we compare the results found by the ANN to those obtained using the electrochemical PEMFC model. The results show that the developed ANN can accurately and quickly predict current and voltage fuel cells at maximum power point for any operating conditions.*

Streszczenie. *W tym artykule zaproponowano śledzenie maksymalnego punktu mocy (MPTT) oparte na sztucznej sieci neuronowej (ANN) dla ogniwa paliwowego z membraną do wymiany protonów (PEMFC). W tym celu wykorzystuje się sztuczną sieć neuronową Radial Basis Function (RBF ANN) do przewidywania napięcia i prądu punktu maksymalnej mocy ogniwa paliwowego w różnych warunkach pracy ogniwa paliwowego. Aby wytrenować proponowaną sztuczną sieć neuronową, przy użyciu sprawdzonego modelu elektrochemicznego ogniwa paliwowego generowany jest zestaw maksymalnych punktów mocy określonych przez odpowiadające im wartości prądu i napięcia. Aby zapewnić wiarygodność ANN, porównujemy wyniki uzyskane przez ANN z wynikami uzyskanymi przy użyciu elektrochemicznego modelu PEMFC. Wyniki pokazują, że opracowana SSN może dokładnie i szybko przewidywać prąd i napięcie ogniw paliwowych w punkcie maksymalnej mocy w dowolnych warunkach pracy.* (***Sztuczna sieć neuronowa RBF do przewidywania maksymalnego punktu mocy ogniwa paliwowego***)

Keywords: Artificial neural network (ANN), Proton exchange membrane fuel cell (PEMFC), Maximum power point tracker (MPPT),.
Słowa kluczowe: sztuczna sieć neuronowa, ogniwo paliwowe, maksymalny punkt mocy

Introduction

The constant depletion of fossil fuels reserves and their harmful atmospheric impact has attracted alternative green energy power sources including solar, wind, hydrogen, and hydropower, to be the most preferred by energy producers [1-3]. Praised by environmentalists and by many large industrial groups, hydrogen is often presented as a pillar of the global energy transition. In this context, the fuel cell, which is the unique converter of the chemical energy of hydrogen into electrical energy, has reached a high level of maturity thanks to the development efforts of several industrialized countries. Several fuel cell technologies exist. The PEMFC (Protons Exchange Membrane Fuel Cell) technology, suitable for car and residential applications due to its low operating temperature, high power density, quiet operation and zero gas emission, concentrates the most research efforts [4].

The output power of a PEMFC is not constant and fluctuates substantially depending on cell temperature, membrane water content, and partial pressures of hydrogen and oxygen gases [5]. In addition, a fuel cell has a non-linear current-voltage characteristic with a single point defined by its corresponding current I_{mpp} and voltage V_{mpp}, where the output power produced, is maximum, like photovoltaic panels [6, 7]. This point is called Maximum Power Point (MPP). A system allowing the fuel cell to operate around the MPP for any operating conditions is needed to continually extract the maximum power from a fuel cell. This system is called Maximum Power point Tracker (MPPT) [8]. MPPT algorithms for fuel cell applications are explained in various ways [9-12]. Because of its easy implementation and its low cost, the Perturb and Observation (P&O) method is by far the most widely utilized in practice in fuel cells [1, 5]. The sluggish convergence speed and oscillations around MPP are the main shortcomings of the P&O method [5,7,13,14]. Artificial neural network (ANN) algorithms, on the other hand, can uncover complicated non-linear relations between independent and dependent variables without requiring a precise mathematical model of the system [5]. Therefore, MPPT controllers based on ANN techniques have been proposed to solve these problems regarding the improvement of the dynamic performance of MPP tracking [15-18].

In this work, a Radial Basis Function Artificial Neural Network (RBF ANN) is proposed to predict the Maximum Power Point of a PEMFC for any operating conditions. Neural networks (RBFN) are simple to design, generalize well, and are unaffected by noisy input [18, 19]. In our study, the proposed RBF ANN calculates the current and the voltage corresponding to the maximum power point for different operating fuel cell conditions (temperature, hydrogen partial pressure, oxygen partial pressure, and membrane hydration rate).

Fuel cell electrochemical model

A proton exchange membrane fuel cell is made up of a proton exchange membrane inserted between two platinum catalyst-coated electrodes. The anode receives hydrogen, where the cathode receives oxygen.

The operating principle of the fuel cell is based on the reverse process of electrolysis of water. A redox process produces electricity, water, and heat by reacting hydrogen and oxygen (Fig.1) [20, 21].

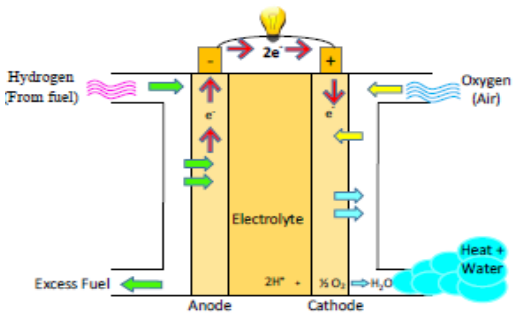

Fig.1. PEMFC principle [22]

All resulting chemical reactions are expressed as follows: Oxidation reaction at the anode:

$H_2 \rightarrow 2H + 2e^-$ (Anode)

Reduction reaction at the cathode:

O_2+4e⁻+4H⁺ → $2H_2O$ (Cathode)

Ref [16] gives the entire chemical reaction of the PEMFC:

$\frac{1}{2}O_2 + 2H^+ + 2e^- \rightarrow H_2O$ +heat + electricity

At standard test conditions (operating temperature of 298.15 K and pressure of 1 atm), the Nernst potential (theoretical thermodynamic potential) of a single fuel cell is on the order of 1.229 V [20, 21].

When the current is non-zero, the voltage of the fuel cell will be lower than the voltage E_{Nerst}.This is mostly owing to irreversible losses namely the ohmic overvoltage, the concentration overvoltage, and the activation overvoltage [20, 24]. The output voltage V_{Cell} of a single cell can be described by the following equation when these losses are taken into account. [20, 24, 25]:

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

Where: E_{Nerst} – Nernst potential (V), V_{act} – activation overvoltage (V), V_{ohm}– ohmic overvoltage (V), V_{con}– concentration overvoltage (V).

The open_ circuit cell potential of E_{Nerst}each cell of the PEMFC is calculated by the Nernst equation. This voltage is a function of the operating temperature T (K) and the partial pressures P_{H_2} of hydrogen (atm) and P_{O_2} of oxygen (atm) [20, 24]. The Nernst equation can be written:

(2) $$E_{Nerst} = 1{,}229 - (8{,}5.10^{-4}).(T-298.15) + 4{,}308.10^{-5}).T.[ln(P_{H_2}) + \frac{1}{2} ln\,(P_{O_2})]$$

The activation overvoltage is due to the start of chemical reactions at the anode and cathode. A part of the available energy is used to break and reform chemical bonds at the electrodes. Activation overvoltage, predominant at low current densities, is given in the model proposed by J.C.Amphlet et al. [20, 24, 25] by the equation:

(3) $$V_{act} = \xi_1 + \xi_2.T + \xi_3.T.\ ln\,(C_{O_2}) + \xi_4.T.\ ln\,(I)$$

where: C_{O_2}- Oxygen concentration in the cathode catalyst interface (mol/cm^3), I- current delivered by the fuel cell (A), ξ_1, ξ_2, ξ_3 and ξ_4 - parametric coefficients determined for the modeled fuel cell stack from theoretical equations of Kinetic, thermodynamic and electrochemical basis. The expression of ξ_2 is given by [24, 26]:

(4) $$\xi_2 = 0,00286 + 0,0002.log\,(A) + 0,000043.log\,(C_{H_2})$$

where: A - cell active area (cm^2) of the membrane, C_{H_2} - effective hydrogen concentration at the anode catalyst sites (mol/cm^3).

Which can be approximated, by the hydrogen concentration at the anode water-gas interface, is expressed as follow [26, 27]:

(5) $$C_{H_2} = \frac{P_{H_2}}{1090000.\exp\left(\frac{77}{T}\right)}$$

The oxygen concentration at the cathode water-gas interface is expressed as [26, 27]:

(6) $$C_{O_2} = \frac{P_{O_2}}{5{,}08.10^6.e^{-\left(\frac{408}{T}\right)}}$$

The ohmic losses are due to the resistance of the bipolar plates to the circulation of electrons and the resistance of electrolyte to the protons flow [27]. The corresponding voltage drop is written as follow [16]:

(7) $$V_{ohm} = I.(R_m + R_c)$$

where: R_m – resistance to proton flow (Ω), R_c – resistance to electrons flow. R_c is usually considered constant while R_m is calculated by the following equation[25,27]:

(8) $$R_m = \frac{\rho_m.t}{A}$$

where: t – polymer membrane thickness (cm), ρ_m – specific membrane resistivity (Ω.cm) . ρ_m is given by [23,24,25,28]:

(9)

$$\rho_m = \frac{181{,}6.[1 + 0{,}003.\left(\frac{I}{A}\right) + 0{,}062.\left(\frac{T}{363}\right)^2.\left(\frac{I}{A}\right)^{2{,}5}]}{\left[\lambda - 0{,}634 - 3.\left(\frac{I}{A}\right)\right].\exp[4{,}18.\left(\frac{T-303}{T}\right)]}$$

where: λ -adjustable parameter, λ has a value ranging from 14 under 100% relative humidity conditions to 22-23 % under ultra-saturated conditions.

The concentration losses linked to the kinetics of gas diffusion across the electrodes become prominent at high current densities, and they are expressed as [16, 20].

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

where: B (V) - empirical coefficient, J - actual current density of the cell (A/cm^2), J_{max} -maximum current density (A/cm^2). B varies depending on the type of fuel cell and its state of operation[20,25].The power P delivered by the fuel cell is equal to the product V. I (W).

The equivalent static electrical circuit of a PEMFC is shown in figure (2):

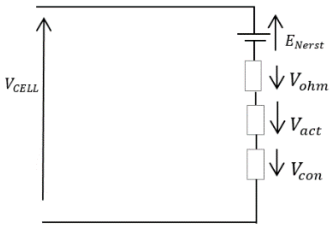

Fig.2. Equivalent static electrical circuit of PEMFC

The voltage of a fuel cell stack formed by N cells in series is expressed as follow:

(11) $$V = N.v_{cell}$$

In this work, we use an Avista SR12 PEMFC. The specifications of this fuel cell taken from its Technical Data Sheet are presented in table 1. MATLAB® software is used to fit the current-voltage of the Avista SR12 and then to calculate the maximum power point for different gas partial pressures, temperature, and membrane hydration rate levels.

Table 1. Avista SR12 PEMFC simulation parameters

Parameter	Value	Parameter	Value
ξ_1	-0.948	A	62.5 cm^2
ξ_3	0.0000722	B	0.15 V
ξ_4	−0.0001061	Rc	0.0003Ω
J_{max}	42 A/cm^2	N	48

Radial Basis Function Artificial Neural Network

The RBFN consists of three layers, the input layer, the hidden layer, and the output layer as shown in figure 3 [29].

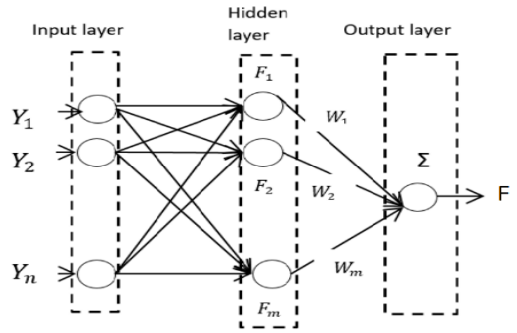

Fig.3. Radial basis function neural network

Each neuron is fully connected to the neurons of the following layer, and the connections are not recurrent. In RBF neural networks, synaptic weights between the input and hidden layers have a unit value [18]. The Gaussian function, whose parameters are the center c and the radius σ, is the most widely employed radial function as an activation function [18, 30]. A Gaussian function responds only to a limited portion of the input space where it is centered. Its general expression is as follows [18, 30]:

(12) $$f(y)=\exp\left(-\frac{(y-c)^2}{2\sigma^2}\right)$$

where: *y* - input scalar and σ > 1.

Each node I in the hidden layer of an RBF neural network represents a Gaussian function Fi defined by its center ci and radius σi [18, 30]. These neurons calculate the distance from the input to their centers and respond with activation in proportion to that distance. The output of the network is a linear combination of the outputs of the hidden layer neurons multiplied by the weights of their respective connections.

The Levenbreg-Marquardt Backpropagation algorithms are most widely used for ANN training. It is a sophisticated gradient algorithm that is used to improve the performance of an ANN by altering the weights of each node and the bias terms until the output value at the output layer as nearly as possible predicts the real outputs, resulting in a reduction in the training error [31].

The mean square error (MSE) performance index is used to verify network convergence. Network converges mean that the training error goal is lower than the predefined MSE [32].

Proposed Artificial Neural Network

To achieve the prediction of maximum power points of a fuel cell, we have opted for the architecture of the RBF neural network with a Gaussian function. The input layer includes four neurons (temperature, hydrogen partial pressure, oxygen partial pressure, and membrane hydration rate) while the hidden layer has ten neurons and the output has two neurons ($V_{mpp}$and I_{mpp}). Figure 4 shows the general schematic of the Neural Network model.

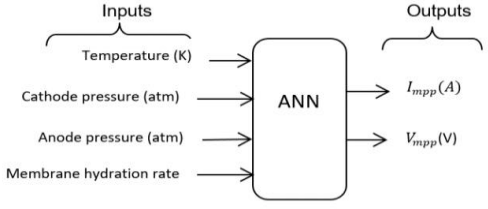

Fig. 4. Proposed ANN inputs outputs

Simulation results

First, we generated training data set samples for the proposed artificial neural network. For this, Training data set containing 108 fuel cell maximum power points defined by their currents and voltage is generated using the electrochemical model detailed above. These samples correspond to varying operating conditions: the operating temperature varies from 290 K to 390 K, gas pressures vary from 0.5 atm to 1.5 atm while the membrane hydration rate varies from 7 and 14. These intervals correspond to the practical PEMFC operating conditions. Training data was divided into a training set of 70% and a test set of 30% of total examples.

The root Mean Square Error (MSE) is used as an indicator of the accuracy of the proposed artificial neural network. Figure 5 shows the MSE evolution.

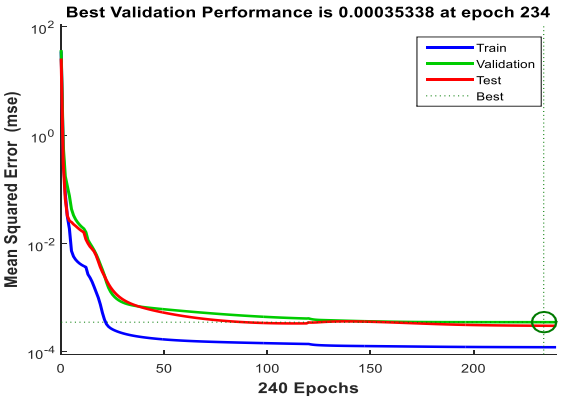

Fig.5. Training Mean Squared Errors evolution

The performance curve plot shows the root mean square error against iterations and it shows the best training performance is 0.00035338 at the 234th iteration. This suggests that the proposed network is precise enough.

This is confirmed by the regression line (Figure 6). This means that after successful training, all data points displayed as circles should be on this line, indicating that the ANN has trained successfully, highlighting the importance of this extremely strong non-parametric process modeling technique.

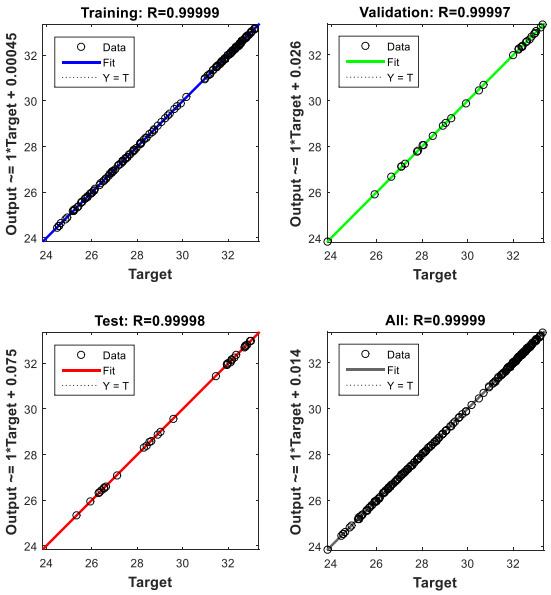

Fig.6. Training regression lines

The developed ANN is finally used to predict fuel cell maximum power points for operating conditions values other than those used for ANN training (Fig 7).

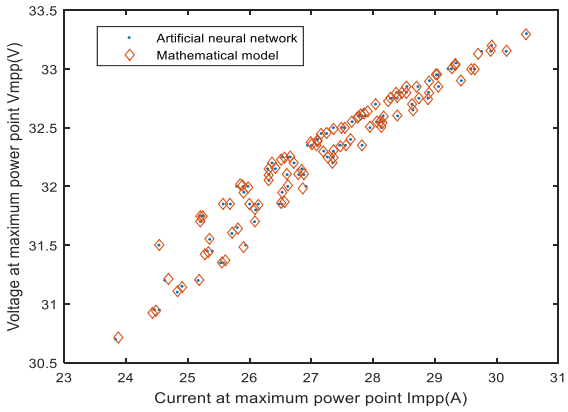

Fig.7. Proposed ANN generalization test

Maximum power points predicted by the proposed RBF Artificial Neural Network are very close to those calculated by the electrochemical model. That means the ANN generalizes well and then it can accurately predict the current and the voltage of the fuel cell Maximum Power Point for any fuel cell operating conditions.

Conclusion

This article demonstrates the capability of an artificial neural network to predict the voltage and the current of the maximum power point of a fuel cell. Indeed, RBF ANN has been developed to predict the maximum power point of the AVISTA SR12 PEMFC whatever the operating conditions (temperature, gas pressures and membrane humidity levels). The developed ANN is characterized by a fast learning with a reduced number of samples. Amphlet's electrochemical model was used to generate the training data set as well as to validate the simulation results. The simulation results show that the proposed ANN can predict with good accuracy the maximum power point of the fuel cell for any operating condition. This work will be used in future study to develop an overall fuel cell MPPT system including fuel cell system, the developed ANN, static converters and corresponding control.

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