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USING ARTIFICIAL IMMUNE SYSTEM FOR OPTIMAL CONFIGURATION OF FUEL CELL-BASED STAND ALONE POWER SUPPLY SYSTEM

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Abstract

For delivering the maximum power output at the load's operating voltage, the fuel cell-based stand alone power supply system has to be configured in terms of number of cells in series, number of cells in parallel, and cell's surface area. In this paper, in order to optimize a stand alone power supply system of proton exchange membrane fuel cell (PEMFC), an artificial immune system (AIS) based on the clonal selection algorithm is proposed. For this aim, a mathematical model for the PEMFC stack is introduced, then, based on this model an AIS code is developed in the Matlab environment. The results manifest that the AIS is a reliable technique for finding the optimal configuration of the fuel cell stack.

Keywords: Fuel cell-based stand alone power supply system; Stack configuration; Artificial immune system**.**

1- Introduction

The hopefulness of very low pollution and relatively high efficiency can be achieved in the fuel cell-based power plant system. Fuel cells are not only characterized by lower pollution and higher efficiency than conventional power sources, but they have superior dynamic response, good stability and low noise. Among different kinds of the fuel cells, because of many advantages such as low operating temperature, high current density, fast response, and zero emission if it is run with pure hydrogen, proton exchange membrane fuel cell (PEMFC) is regarded as an immense alternative for distributed sources of energy in the coming years.

In the fuel cell-based stand alone power supply systems to work efficiently, the maximum power output must be delivered at the load's operating voltage. So, the fuel cell stack configuration has to be optimized in terms of number of stack cells in series, number of stack cells in parallel, and cell's surface area. By the help of an optimization technique, the optimal stack configuration can be obtained. Although various aspects of the PEMFC have been considered by many researchers, but the stack sizing and configuration has received little attention. The focus of this paper is the stack configuration issue.

The evolutionary computation technique based on genetic algorithm (GA) has been recently attracted much attention in the study of fuel cell systems [1], [2], [3], [4], and [5]. Although the GA gives better results than the traditional methods, but still have some deficiencies. For instance, premature convergence and falling into local extremums are two drawbacks.

Inspired by immune system (IS) and its principles, artificial immune system (AIS) has been recently regarded as an efficient candidate to solve optimization problems. Research studies have indicated that the AIS-based algorithms are comparable against other natural-inspired algorithms in order to solve optimization problems [6]. In our study, an optimization method based on AIS for PEMFC stack configuration is developed.

This paper is organized as follows: In Section 2, the PEMFC model and stack configuration is discussed. Section 3 is concerned with the study of the artificial immune system. Results are presented in section 4 and ultimately, conclusion is stated in Section 5.

2. Mathematical model of the PEMFC stack

In normal operation of a PEMFC, in order to get a continuous electrical power, the hydrogen gas has to be fed constantly to the anode (negative electrode) compartment and an oxidant, usually from air, has to be fed constantly to the cathode (positive electrode) compartment. In the anode and at the presence of platinum, which is usually used as catalyst, the hydrogen gas releases electrons and H^+ ions (or protons). The polymer electrolyte only allows the protons to pass through it, and not electrons. Via an external circuit, the electrons move from the anode to the cathode and accordingly an electrical current flows through the circuit. At the cathode, oxygen reacts with the electrons taken from the external circuit and the protons from the polymer electrolyte and produces water. Total reaction of the cell can be shown by the following expression.

$$H_2 + 0.5O_2 \xrightarrow{pt} H_2O + Electricity + \text{Heat} \quad (1)$$

In a hydrogen fuel cell, though the theoretical open circuit voltage is a value of about 1.2 V [7] but, when a fuel cell is made and put to use, due to a number of voltage drops the voltage is less than this value.

Many fuel cell models have been developed in the literature [7], [8], [9], [10], [11], [12], [13], [14], and [15]. The one used in this investigation is adopted from [7]. Basic expression for the voltage of the PEMFC system can be given by:

$$V_s = Z \times \left(E_0 - \eta_{ohm} - \eta_{act} - \eta_{con}\right) \quad (2)$$

In it, V_S is the output voltage (V), Z is the number of fuel cells connected in series, E_0 is the ideal standard voltage (V), and η_{ohm}, η_{act} and η_{con} are the voltage drops (V) which are caused when a current is drawn from the fuel cell by the load.

The ohmic loss η_{ohm} is linearly proportional to the current density. This voltage drop is the straightforward resistance to the flow of electrons through the material of the electrodes and the various interconnections, as well as the resistance to the flow of ions through the electrolyte [7]. According to the Ohm's law, it is given by:

$$\eta_{ohm} = ri \quad (3)$$

where r is the area specific resistance of the fuel cell ($k\Omega\ cm^2$) and i is the fuel cell current density ($mA\ cm^{-2}$).

The activation loss η_{act} is a highly non-linear voltage drop which is caused by the sluggishness of the reactions taking place on the surface of electrodes. This is given by:

$$\eta_{act} = A\ln\left(\frac{i}{i_0}\right) \tag{4}$$

In it, the constant A is called Tafel slop (V) and i_0 is usually called the exchange current density ($mA\ cm^{-2}$), at which the voltage drop begins to move from zero.

The concentration loss η_{con} results from the change in the concentration of the reactants at the surface of electrodes. Due to the reduction in concentration is the result of a failure to transport sufficient reactant to the electrode surface, this type of loss is also often called *mass transport loss* [7]. It is expressed by the following expression.

$$\eta_{con} = -B\ln\left(1-\frac{i}{i_L}\right) \tag{5}$$

where B is a concentration loss constant (V) and i_L is the limiting current density ($mA\ cm^{-2}$), at which the cell voltage will fall quickly.

Crossover and internal currents are other causes for the fuel cell voltage drop. Reasons for this are the waste of fuel that passes directly through the electrolyte producing no electrons and electron conduction through the electrolyte and not passing through the electrodes. This results an increasing effect on the current withdrawn from the cell by value of i_n.

By introducing the internal and fuel crossover equivalent current density and combining (2), (3), (4), and (5), the relationship between the fuel cell voltage and current can be shown by:

$$V_s = Z\left(E_0 - r(i+i_n) - A\ln\left(\frac{i+i_n}{i_0}\right) + B\ln\left(1-\frac{i+i_n}{i_L}\right)\right) \tag{6}$$

To produce more power output, fuel cells have to be connected together forming a stack. A typical PEMFC stack is illustrated in Figure1.

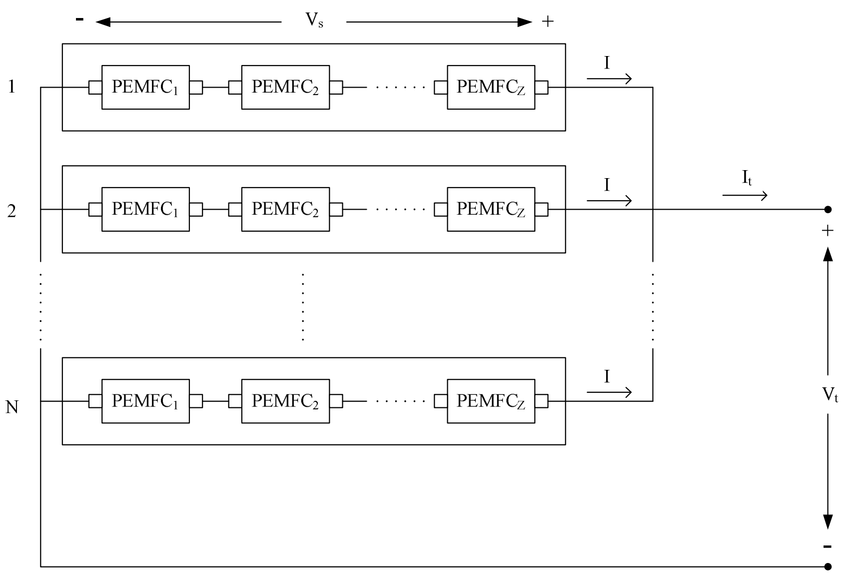

Figure 1. Schematic of a PEMFC stack.

The relationship between the terminal voltage and current can be represented by:

$$V_t = Z\left(E_0 - r\left(\frac{I_t}{NS} + i_n\right) - A\ln\left(\frac{\frac{I_t}{NS} + i_n}{i_0}\right) + B\ln\left(1 - \frac{\frac{I_t}{NS} + i_n}{i_L}\right)\right) \tag{7}$$

In it, V_t is the terminal voltage (V), I_t is the terminal current (mA), N is the number of stack cells in parallel, and S is the cell's area (cm^2) which plays an important role in the power generation.

In this research, the main goal is to design a power supply system to provide dc electricity for a single dwelling in a remote area of a developing country. The system uses solar hydrogen technology, where a fuel cell stack is used to convert hydrogen into dc electricity. The system load is estimated to be 730 kW per year on 12 V dc [2]. The fuel cell stack has to be configured so that it can provide the design requirements of delivering the right amount of power at 12 V dc. Moreover, the physical size of the fuel cell stack has to be suitable for using in a family house. This work can be accomplished by optimization of the PEMFC stack design by searching for the best configuration in terms of number of stack cells in series Z, number of stack cells in parallel N, and cell's surface area S. In order to conquer this problem artificial immune system is proposed. In each optimization problem the definition of an objective function (performance criterion) is necessary. The objective function will specify on how to perform the identification process. In this paper, the objective function F is defined based on how far the fuel cell stack voltage at maximum power point is from the load's operating voltage. To achieve this goal the objective function is defined according to Eq. (8).

$$F = \alpha_1\left(1 - \frac{P_{\max}}{P_{ref}}\right)^2 + \alpha_2\left(1 - \frac{V_t(P_{\max})}{V_{ref}}\right)^2 \tag{8}$$

In which, P_{max} is the maximum output power, $V_t(P_{max})$ is the output voltage at the maximum power, P_{ref} is the load's power, and V_{ref} is the load's operating voltage, α_1 and α_2 are used to control the weighting of $\left(1 - \frac{P_{\max}}{P_{ref}}\right)^2$ and $\left(1 - \frac{V_t(P_{\max})}{V_{ref}}\right)^2$, respectively. For this study, $P_{ref} = P_{max} = 730$ kW and $V_{ref} = 12$ V.

3. Artificial immune system

As an efficient and powerful natural protection system, the biological immune system can generate multiple antibodies from antibody gene libraries and keep it alive even if the foreign pathogens are unknown. The primary immune theory model is the regulation theory of the biological immune system, which consists of immune density regulation mechanism and network regulation mechanism [16], [17]. The theory indicates that the biological immune system can adjust the generation of antibodies and balance the quantity of the multiple kinds of antibodies. When antigens invade, the antibodies that match these antigens are activated and produce more antibodies to restrain the antigens. Then the immune system achieves a new balanceable state.

Artificial immune system (AIS) is a computational system inspired by the principles and processes of the vertebrate immune system. The algorithm typically exploits the immune system's characteristics of learning and memory to solve a problem. Nowadays due to promising results the immune systems and algorithms have gained much attention and wide applications in different fields [18], [19], and [20]. Clonal selection algorithm [21] as one of the existing immunity-based algorithms, inspired by the clonal selection theory, is most commonly applied to the optimization domains. Affinity proportional reproduction and affinity maturation are two key features of the clonal selection. An antigen chooses some cells to acquire their clone. The selection rate of each cell is directly proportional to its affinity with selective antigen. If an antigen has a high affinity, number of offspring of this antigen is high. The mutation rate is inversely proportional to its affinity with an antigen [22].

In this work, in order to optimize the stack configuration, an artificial immune system is proposed. This method is based on the clonal selection algorithm. The steps of the proposed algorithm used in this study to get the optimal configuration are shown as below:

Step 1. Initially a population of antibodies is randomly produced in the feasible region. Each antibody consists of *Z*, *N*, and *S*.

Step 2. The antibodies are inserted into the model given by Eq. (7), and the voltage versus current characteristic is calculated. The value of the objective function (antigen) is calculated by using of Eq. (8) for each antibody. The affinity of each antibody is equal to the normalized objective function value and is computed by:

$$Aff_j = \frac{F_{\max} - F_j}{F_{\max} - F_{\min}} \tag{9}$$

In it, Aff_j is the affinity of the j^{th} antibody, F_j is the objective function value of the j^{th} antibody, and F_{max} , F_{min} are the maximum and minimum objective function values in the current population, respectively.

Step 3. Based on their affinity, the population is divided into three classes (high-affinity subset, medium-affinity subset and low-affinity subset) using the following equation [23].

$$antibody\ class = \begin{cases} high-affinity & if \quad Aff_j \geq Aff_{mean} + 1.5\times\sigma \\ medium-affinity & if \quad Aff_{mean} - 1.5\times\sigma < Aff_j < Aff_{mean} + 1.5\times\sigma \\ low-affinity & if \quad Aff_j \leq Aff_{mean} - 1.5\times\sigma \end{cases} \tag{10}$$

In which, Aff_{mean} and σ are the mean and the standard deviation of the affinity of the whole population, respectively.

For generating a pool of clone, the antibodies in the high and medium-affinity subsets are cloned. The number of clone depends on the antibody's affinity. The higher the affinity, the more the clone will produce. According to the following equation, the number of clone for each antibody is determined [23].

$$N_{cj} = \delta \times Aff_j \tag{11}$$

In it, N_{cj} is the clone size of j^{th} antibody and δ is the maximum clone size of an antibody in each iteration.

Step 4. The clones have to be mutated. Mutation rate for each clone is inversely proportional of its affinity. The clones are mutated by Eq. (12) [23].

$$c' = c + m \times random \times \eta \tag{12}$$

$$m = \exp(-\mu \times Aff_j) \tag{13}$$

In which, *c* is the clone, *c'* is the mutated clone, *m* is the mutation rate, *random* is a random number between -1 and 1, and η is the step factor which firstly set to a value depends on the bound of the variables. Step factor is reduced during iteration by a factor θ. In this investigation, the factor θ is selected as the following decreasing linear function.

$$\theta(t) = \theta_{\max} - (\theta_{\max} - \theta_{\min}) \times \frac{t}{t_{\max}} \tag{14}$$

where *t* is the iteration index, t_{max} is the maximum iteration times, and θ_{max} , θ_{min} are the initial and final values for the θ, respectively. Therefore,

$$\eta = \theta \times \eta \tag{15}$$

In Eq. (13), the value of μ has a significant effect on the clonal selection performance. If the value of the μ is selected too big, only very few antibodies are exposed to mutation and diversity of the population can't be guaranteed, and vice versa.

<u>Step 5.</u> According to Eq. (9) the affinity of each clone is computed and then, the best mutated clone is replaced with its parent.

<u>Step 6.</u> The antibodies in the low-affinity subset are eliminated and replaced by randomly generated antibodies.

<u>Step 7.</u> Step 2 to step 6 are repeated until the stop criterion is met, which can be that the maximum iteration times are reached or the minimum objective function value is satisfied.

4. Results

In order to find the best configuration of the PEMFC stack, the AIS code is developed in the Matlab environment. An educational solar hydrogen test rig [2] is used to provide the load's power. The parameters of this fuel cell are given in Table 1.

Table 1. Fuel cell model parameters.

Parameter	Value
E_0	1.04 V
A	0.05 V
i_n	1.26 mA cm^{-2}
i_0	0.21 mA cm^{-2}
r	98×10^{-8} kΩ cm^2
B	0.08 V
i_L	129 mA cm^{-2}

In this investigation the lower and upper bounds of the stack parameters are given by $1 \leq Z \leq 50$, $1 \leq N \leq 50$, and $10\ cm^2 \leq S \leq 400\ cm^2$, the weighting factors of α_1 and α_2 are set to 1 and the adjusted parameters for the AIS are given by population size = 20, δ = 10, μ = 4, θ_{min} = 0.5, θ_{max} = 1.5, and t_{max} = 70.

Table 2 shows the performance of AIS algorithm in comparison with the results obtained by GA [2]. As can be seen AIS yields a smaller value for objective function than GA. So, the performance of AIS is better than GA. The convergence process of the AIS, which indicates the best objective function value versus the iteration times, is illustrated in Figure 2. As can be seen, the convergence speed is fast so that the optimization process is converged to the optimal values after about 20 iterations.

Table 2. Optimal values for the fuel cell stack design parameters obtained by the AIS.

Variable	**AIS**	**GA**
Number of stack cells in Series, *Z*	22	21
Number of stack cells in Parallel, *N*	8	1
cell's area, *S*	18.82 cm^2	156.25 cm^2
F	4.287×10^{-4}	7.430×10^{-4}

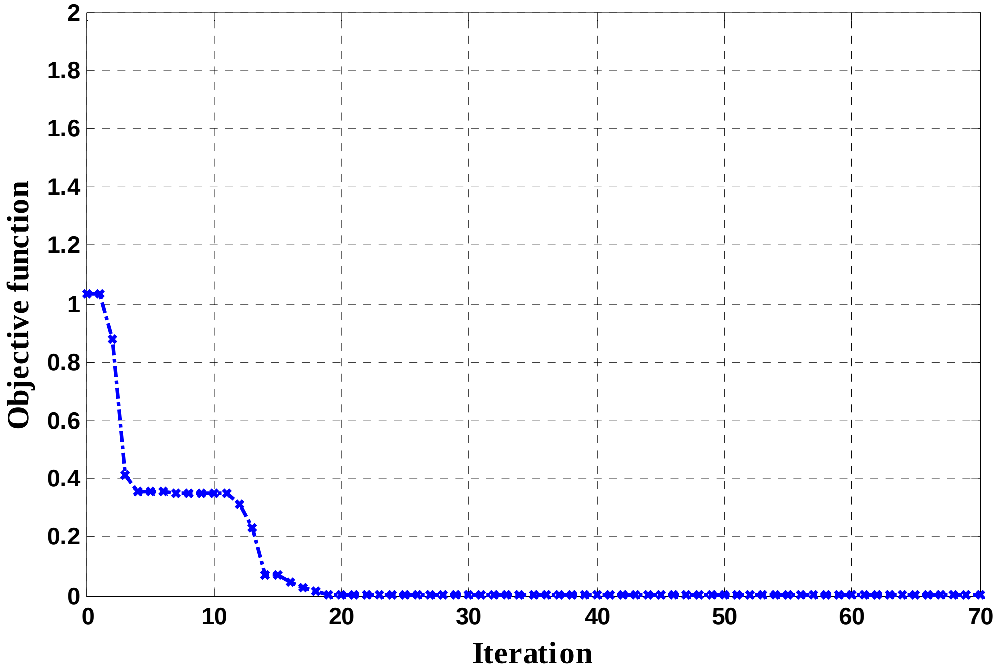

Figure 2. Convergence process of the AIS during the optimization process.

In order to confirm the performance of the PEMFC stack designed using artificial immune system, after the optimization procedure the optimal parameters are fed back to the stack mathematical model to perform performance simulation. Figure 3 and Figure 4 show the voltage versus current and the power versus voltage characteristics of the stack. It is obvious that using optimal parameters found by AIS, the maximum power point occurs at the load's operating voltage.

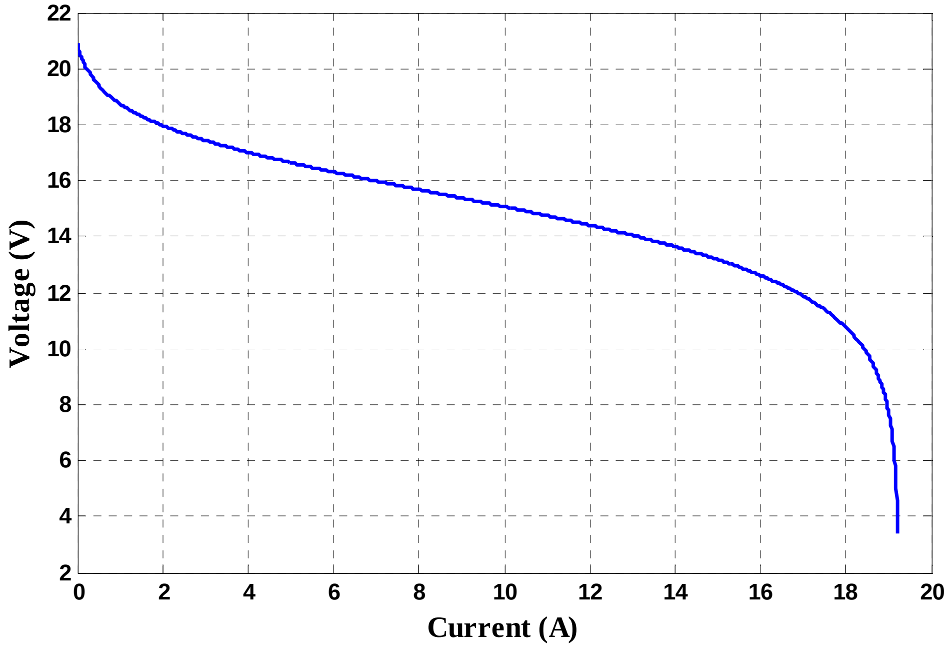

Figure 3. The voltage versus current characteristic of the optimized PEMFC stack.

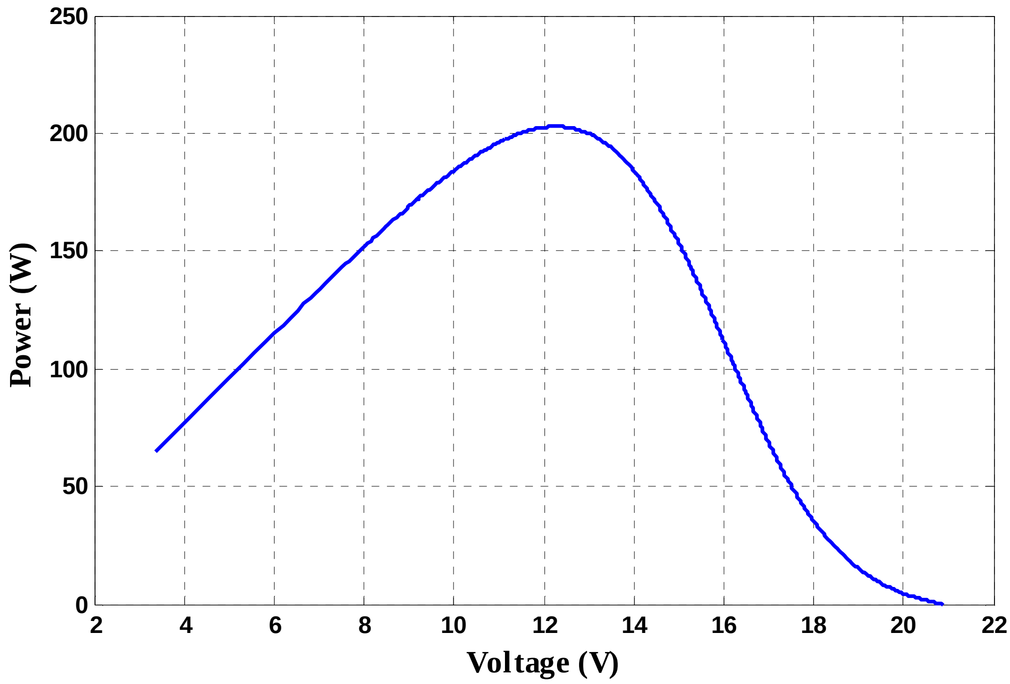

Figure 4. The power versus voltage characteristic of the optimized PEMFC stack.

5. Conclusion

It this paper, in order to optimally configure a fuel cell stack to deliver its maximum power output at the load's operating voltage, an artificial immune system based on the clonal selection algorithm is proposed. It is shown that the optimization process is converged after about 20 iterations to the best configuration. The optimum solution is confirmed by feeding it to the stack model and performing current versus voltage and power versus voltage characteristic simulations. Results show that AIS is an effective and reliable technique for configuration of the fuel cell stack and can be used to solve other complex optimization problems of the fuel cell system.

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