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Proton exchange membrane (PEM) fuel cell stack configuration using genetic algorithms

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Abstract

For stand alone power supply systems based on fuel cells to work efficiently, the fuel cell stack has to be configured so that it delivers the maximum power output at the load's operating voltage. This paper discusses how genetic algorithms were applied to optimise a proton exchange membrane fuel cell stack design by searching for the best configuration in terms of number of cells and cell surface area. First, a mathematical simulation model of the fuel cell was developed. The model parameters were obtained by fitting the mathematical model to experimental data. A genetic algorithm code was then developed. The code is based on the fuel cell stack model as an evaluation measure for the fitness of the solutions generated. Results are presented confirming the effectiveness of using the genetic algorithm technique for fuel cell configuration.

Keywords: Fuel cell; Modelling; Polarisation; Genetic algorithms

1. Introduction

Proton exchange membrane fuel cells (PEMFC) offer a number of advantages compared to other types [1–5]. Many papers have been published on different aspects of PEM fuel cells [6–9], but the issue of stack sizing and configuration has received little attention.

Section 2 of this paper introduces the fuel cell model. In section 3, the parameters were fitted using experimental data. Section 4 discusses the fuel cell stack design, while the use of genetic algorithms to optimise the stack is presented in Section 5. Results obtained are given in Section 6.

2. Fuel cell modelling

Many fuel cell mathematical models are available in the literature [10–15]. The one used in this work was adapted from [16]:

$$V_S = Z(E_O - \eta_{act} - \eta_{ohm} - \eta_{con}) \qquad (1)$$

where, V_S is the stack voltage, Z is the number of series connected cells in the stack, E_O is the open circuit voltage, and η_{act}, η_{ohm}, η_{con} are the voltage drops occurring when the load draws a current from the fuel cell stack.

The theoretical open circuit voltage for a hydrogen–oxygen fuel cell is about 1.2 V [16]. Practically, the operating voltage is less than this value due to a number of irreversibilities.

The activation over potential η_{act} is due to voltage lost in activating the chemical reactions to take place at the fuel cell electrodes. This over potential is important at low currents and can be expressed as:

$$\eta_{act} = A \ln\left(\frac{i}{i_0}\right) \qquad (2)$$

where A is called Tafel slope and is measured in volts, i is the fuel cell stack current density in mA/cm^2, and i_0 is the exchange current density in mA/cm^2.

The ohmic loss η_{ohm} is due to the electrolyte resistance to the flow of ions across it, and the resistance of the electrode material to the flow of electrons. The ohmic losses is linearly proportional to the stack current and is given by the following simple expression:

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

where r is the area specific resistance of the fuel cell measured in kΩ cm^2.

The concentration loss η_{con} is related to the consumption of reactants by the fuel cell. As the reactants are used by the fuel cell, their concentration changes at the surface of the cell electrodes causing a drop in operating voltage.

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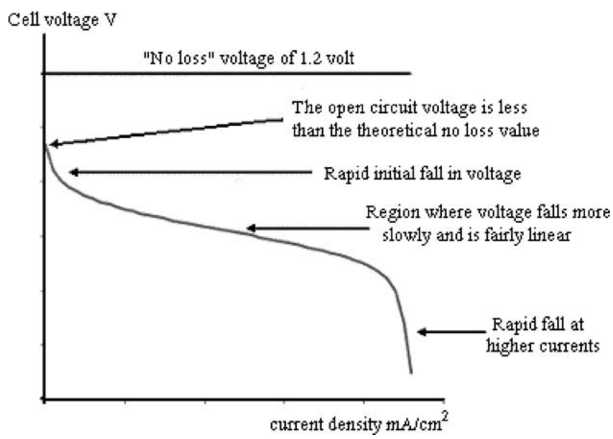

Fig. 1. *I–V* characteristic of a typical fuel cell.

Concentration loss is related to the fuel cell current by the following equation:

$$\eta_{\mathrm{con}} = -B \ln\left(1 - \frac{i}{i_{\mathrm{L}}}\right) \quad (4)$$

where B is a concentration loss constant given in volts, and i_{L} is the limiting current density at which the cell voltage will fall rapidly. i_{L} is measured in mA/cm^2.

Other causes for the fuel cell voltage drop are fuel crossover and internal currents. 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 will have an increasing effect on the current withdrawn from the cell by a value of i_n.

By combining Eqs. (1)–(4) and introducing the internal and fuel crossover equivalent current density, the mathematical polarisation curve model of the fuel cell will be:

$$V_{\mathrm{S}} = Z\left[E_{\mathrm{O}} - A \ln\left(\frac{i + i_n}{i_0}\right) - r(i + i_n) + B \ln\left(1 - \frac{i + i_n}{i_{\mathrm{L}}}\right)\right] \quad (5)$$

A plot of Eq. (5) comparing the ideal case with a typical current voltage characteristic of a fuel cell is presented in Fig. 1.

3. Fuel cell mathematical mode fitting

For the mathematical model given by Eq. (5) to be used for fuel cell simulation and design, the values of the following parameters have to be obtained: E_{O}, A, I_n, I_{O}, R, B, I_{L}. To accomplish this, an experiment was set up based on an educational solar hydrogen test rig. A sketch of the apparatus is shown in Fig. 2. It consists of two 10 cm^2 fuel cells that can be connected either in parallel or series. A solar module of four cells was used to power a 25 cm^2 electrolyser to produce hydrogen at a maximum rate of 28 ml/min.

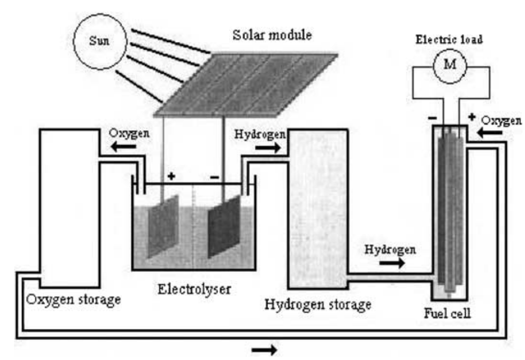

Fig. 2. Sketch of a PV-H_2 test rig.

The hydrogen is stored in a cylindrical tank ready for use by the fuel cells. To examine the fuel cell at different loads, selectable resistances ranging from 0.3 to 100 Ω are connected to fuel cell terminals. Current and voltage at each load are displayed on LCD panels of a digital ammeter/voltmeter.

Successive measurements of the fuel cell current and voltage were recorded for different loads. The open circuit voltage was first measured at no load giving a value of 0.955 V. Then the resistances were decreased in a sequence of 100, 50, 20, 10, 5, 2, 1, 0.5, 0.3 Ω. Fig. 3 shows *I–V* plot of the measured values.

The experimentally measured *I–V* data were fitted to Eq. (5). This was accomplished by a computer code developed using the optimisation toolbox of the MATLAB software.

All the parameters in Eq. (5) were left free. Values obtained of the parameters agreed well with those found in the literature and are given in Table 1.

4. Fuel cell stack configuration

Fuel cells can be connected in series and parallel forming a stack to produce more power output. The cell's area is also a key factor in increasing this power.

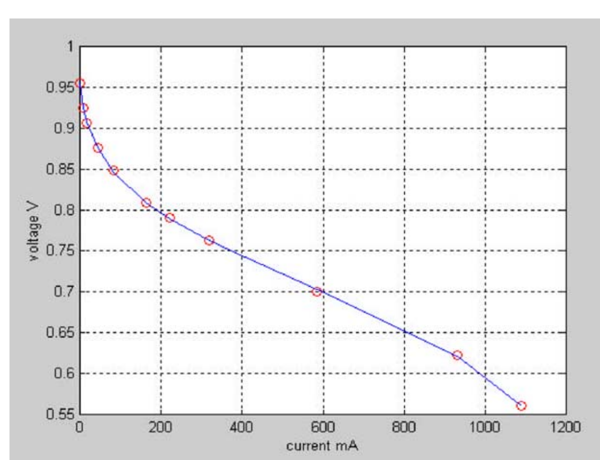

Fig. 3. Experimental *I–V* curve of fuel cell.

Table 1
Fuel cell model fitted parameters

Parameter	Value
E_O (V)	1.04
A (V)	0.05
I_n (mA/cm^2)	1.26
I_O (mA/cm^2)	0.21
R (kΩ cm^2)	98×10^{-6}
B (V)	0.08
I_L (mA/cm^2)	129

A research project aimed to design a power supply system to provide dc electricity for a single dwelling in a remote area of a developing country. The system used solar hydrogen technology, where a fuel cell stack will be used to convert hydrogen into electricity. The system load was estimated to be 730 kW h per year operating on 12 V dc.

The task was to configure the fuel cell stack so that it fulfils the design requirements of delivering the right amount of power at 12 V dc. In addition, the fuel cell stack should be of acceptable physical size to be used in a family house. However, numerous trials were necessary in order to choose the optimal design parameters (number of cells in series and in parallel and the cell's surface area). In order to overcome this problem, genetic algorithms were used.

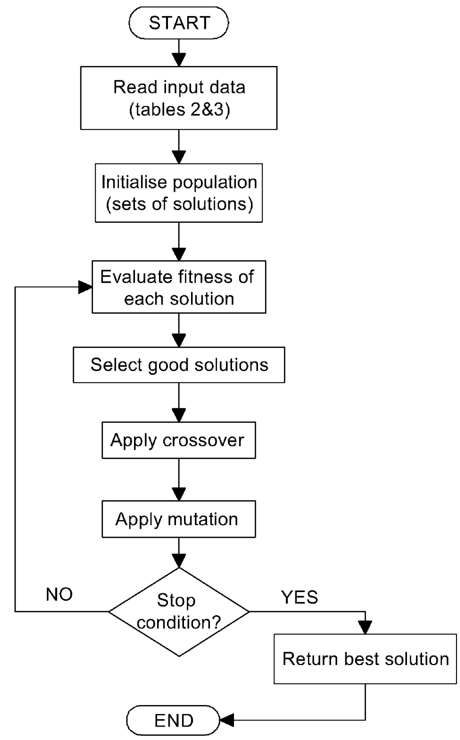

Fig. 4. The genetic code to obtain the fuel cell optimal parameters.

5. Fuel cell stack design using GAs

Genetic algorithms are search methods that can be used to solve optimisation problems by implementing powerful search techniques to find an optimal solution within a large search space (possible solutions to the problem).

Genetic Algorithm techniques are based on natural biological evolution [17]. A genetic algorithm works by generating a large set of possible solutions to a given problem. It then evaluates each of these solutions, and decides on a "fitness level" which is closer to the optimal solution. These solutions then breed new solutions. The parent solutions that were more fit are more likely to reproduce, while those that were less fit are less likely to do so. GA operators, mainly crossover and mutation, achieve the reproduction of solutions [18].

Crossover combines the features of two parent chromosomes (solutions) to form two new similar children (new solutions) by swapping corresponding segments of parents [19]. Mutation is done by randomly changing one or more genes (parameters within a solution), by a random change with a probability equals to mutation rate. Crossover is aimed at exchanging information between different potential solutions, while mutation is aimed at introducing some extra variability into the population [20].

To design the fuel cell stack using genetic algorithms, or in other words to optimise the three design parameters which are number of stack cells in series, number of stack cells in parallel, and cell's surface area, a MATLAB computer code was developed. The code starts with generating solutions by randomly selecting values for the design parameters between upper and lower limits provided by designer. These solutions are evaluated using the fitness function. The fitness function is based on the fuel cell mathematical model given by Eq. (5). The solutions are inserted into the model, and the *I–V* characteristic is calculated. The penalty approach [20] was used to penalise solutions not producing the required amount of power. Those that do so are ranked using a linear rank selection technique [18] according to the nearness of stack operating voltage at the maximum power point to 12 V. Then, a stochastic universal sampling method [20] was used to select some of the good solutions to form a new population of solutions. Crossover and mutation are then applied to the selected solutions to produce new off springs. This process continues till the specified number of generations is reached.

A flowchart of the steps of the genetic code used to get the optimal parameters is shown in Fig. 4. The parameters values of genetic algorithms used are given in Table 2. Table 3 gives the upper and lower limits of the optimised parameters.

Table 2
Values of genetic algorithm parameters

Parameter	Value
Number of generations	200
Population size	20
Number of parameters	3
Crossover rate	90%
Mutation rate	10%

Table 3
Upper and lower values of the parameters to be optimised (search space)

Parameter	Lower limit	Upper limit
Number of stack cells in series	1	50
Number of stack cells in parallel	1	50
Cell's area (cm^2)	10	400

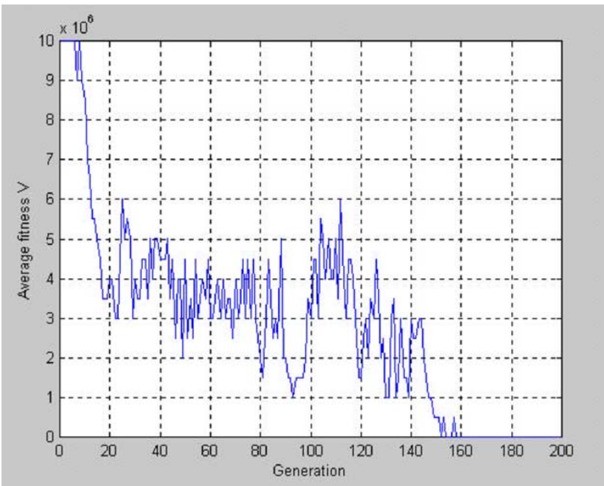

Fig. 5. Solutions average fitness.

6. Results

By executing the fuel cell stack design genetic code, solutions were generated, evaluated for their fitness, and then genetically modified to converge to the optimal parameter values. Fig. 5 shows the average fitness of the 20 solutions processed at each generation. Here the lower the fitness value the better the solution is. This is so because the fitness is measured in terms of how far the fuel cell stack voltage at maximum power point is from the load's operating voltage. It is clear that as the number of generations approaches the end, the code gets closer to the optimal solution.

Fig. 6 illustrates the convergence of the genetic code towards the optimal solution. This is clear that the difference between the stack's voltage and the load's operating voltage at generation 200 is just 1.5×10^{-6} V. This corresponded to the optimal design parameters, which are given in Table 4.

In order to verify the performance of the fuel cell stack designed using genetic algorithms, the optimal design parameters values were fed back to mathematical polarisation curve model to perform performance simulation. Fig. 7 shows the

Table 4
Optimal values for the fuel cell stack design parameters

Parameter	Optimal value
Number of stack cells in series	21
Number of stack cells in parallel	1
Cell's area (cm^2)	12.5 × 12.5

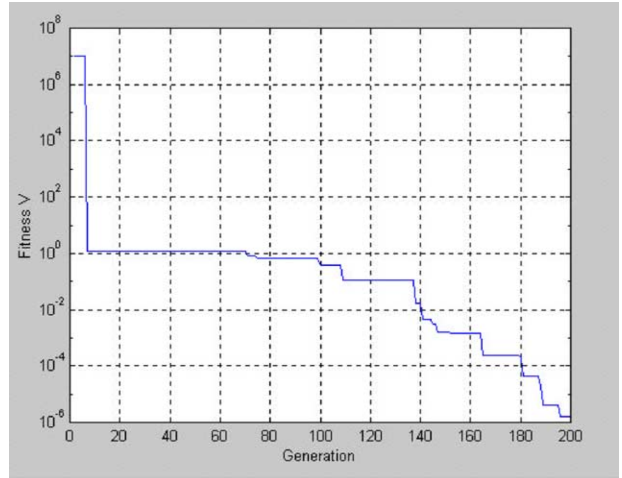

Fig. 6. Fitness of best solution during the generations.

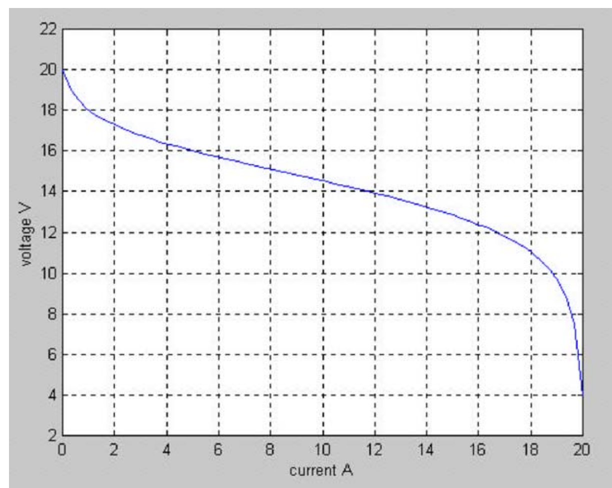

Fig. 7. Fuel cell stack polarisation curve using optimal parameters obtained by GA code.

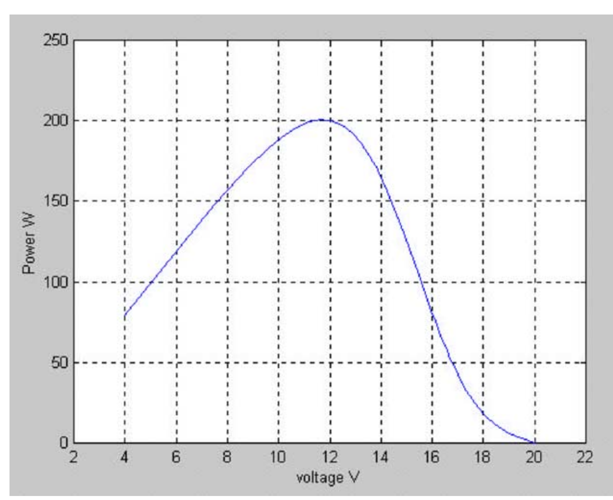

Fig. 8. Voltage power characteristics of the fuel cell stack using the optimal parameters from GA.

current voltage characteristics of the stack, while the power voltage characteristic is presented in Fig. 8.

7. Conclusion

In this paper, a mathematical polarisation curve model for proton exchange membrane fuel cell was presented. The model was verified against experimental data, and offers a very useful tool for fuel cell behaviour simulation. The paper also described how a fuel cell stack can be configured using genetic algorithms. A genetic algorithm code was developed using MATLAB. The code evaluation function was based on the simulation model as a measure for the solutions fitness. For the design case studied in this paper, the genetic code took only 2 min to arrive to an optimal solution. This solution was verified by feeding it to the fuel cell model and performing current–voltage and power–voltage characteristic simulations.

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