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Full Length Research Paper

Genetically tuning of lead-lag controller in order to control of fuel cell voltage

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The aim of this article is to introduce, implement and control the voltage of one of the most important types of fuel cell, namely proton exchange membrane fuel cell (PEMFC) during system load variations. Fuel cell output voltage should be kept in a constant value against the load variations, and a controller should be designed for this purpose. Here, the Lead-Lag Controller is used in which its coefficients are optimized based on genetic algorithm. In order to use this algorithm, at first, problem is written as an optimization problem which includes the objective function and constraints, and then to achieve the most desirable controller, Genetic Algorithm (GA) method is applied to solve the problem. Simulation results are done for various loads in time domain, and the results show the efficiency of the proposed controller in contrast to the previous controllers. Simulations show improved accuracy of the proposed controller performance to achieve this goal.

Key words: Proton exchange membrane fuel cell (PEMFC), genetic algorithm, lead lag controller-optimization problem.

INTRODUCTION

Proton exchange membrane fuel cells (PEMFCs), include a cathode and an anode, and a proton leading between the anode and cathode is as an electrolyte. Hydrogen gas (H_2), which is obtained from the methanol (CH_3OH), is inserted to the end of the anode blade (negative electrode), and also oxygen or air to the end of the positive electrode of cell (cathode) (Zhigun et al., 2005).

To produce electrical energy from fuel cell, it is essential that the output voltage of cell kept constant for different loads to supply high quality power to the loads. But fuel cell output voltage changes for different loads. In order to keep cell voltage constant, using a controller is vital. The most simple type of controller that can be used is a PID.

According to Zhigun et al. (2005), a type of fuzzy controller to control the fuel cell output voltage is proposed. In order to control the voltage and current of the fuel cell, Anucha et al. (2007) used BP and RBF networks. The speed and accuracy of the proposed algorithms, (Anucha et al., 2007) for this system are satisfactory. According to Yanjun et al. (2006), artificial neural networks are used to control the temperature of the fuel cell. To achieve good and efficient control, Almeida and Simoes (2003) utilized an optimized neural controller with Cerebellar Model Articulation Controller (CMAC). According to Hossein et al. (2009), a reinforcement learning adaptive controller for this system is presented, which adjusts controller coefficients online during load variations.

Studied fuel cell, is of the multiple fuel cells, but it is assumed that anode and cathode mass has been compressed in anode and cathod as a fuel cell (Liyan et al., 2006).

Each proposed method are used to control only one parameter of the fuel cell, which in the methods fuzzy or neural network are used. Some of these systems initially detect and then control the system, that in turn this will make slow the control work and in some cases causing long transient response. According to Hossein et al. (2009), controller which also has an adaptive PID controller, output results depend heavily on initial conditions.

In this paper, a simple Lead-Lag Controller for fuel cell voltage control has been used. Except, the controller design has not been achieved through trial and error. But the problem has been proposed as an optimization

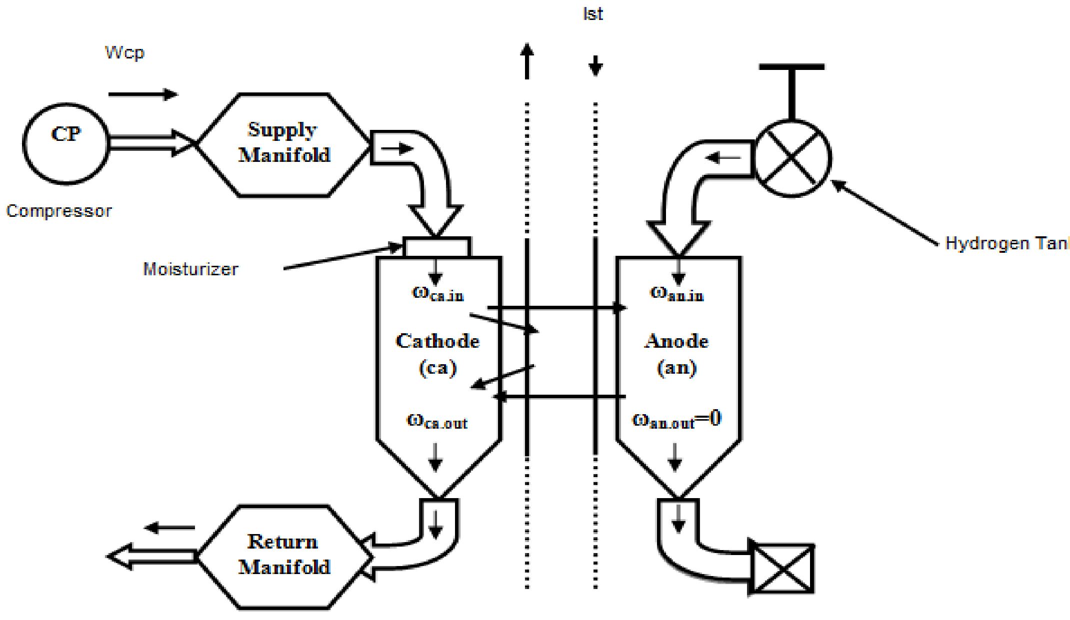

Figure 1. Simplified Fuel Cell reactant supply system.

problem and then solved by using genetic algorithm. The advantages of the proposed control, includes the followings: controllers are simple, being robustness against load changes, having the desired control features, fast transient response and zero steady error.

Dynamic model of fuel cell

To study the dynamic model of the fuel cell, firstly, the general schematic, structure and function of the fuel cell should be studied. The schematic system of the fuel cell that will be studied in this paper is shown in Figure 1. The mass of the anode and cathode in the figure are considered as a sole compression of anode and cathode (Liyan et al., 2006).

In this paper, the dynamic model of the fuel cell is considered according to the reference (Zhigun et al., 2005). The output voltage of the fuel cell is obtained by subtracting the voltage drops from the regressive voltage. Equation 1 shows how to calculate the fuel cell output voltage (Liyan et al., 2006; Larminie and Dicks, 2001; Zhan et al., 2007).

$$V_s = n(E_{reversable} - V_{act} - V_{ohmic} - V_{con}) \tag{1}$$

Where, V_s is the accumulated fuel cell output voltage in volts, n is the existing cells in the accumulated fuel cell, V_{act} is the voltage drop resulting from anode and cathode activity in volts, V_{ohmic} is the ohmic voltage drop in volts, which is a certain amount of resistance in the transfer of electrons and protons in the electrolyte between the anode and cathode. V_{con} is resulting from the mass transfer of oxygen and hydrogen. $E_{reversable}$ in Equation 1 is calculated through the following Equations 1 and 9:

$$E_{reversable} = 1.229 - 0.85\times10^{-3}(T - 298.15) + 4.3085\times T\times[\ln(PH_2 + 0.5\ln(PO_2)] \tag{2}$$

Where, T is the cells temperature in Kelvins, PH_2, PO_2 are effective partial pressure (atm) of hydrogen and oxygen gases respectively that can be calculated by the following equation.

$$PO_2 = P_c - P_{H_2o}^{sat} - P_{N_2}^{channel}\exp\left(\frac{0.291\left(\frac{i}{A}\right)}{T^{0.932}}\right) \tag{3}$$

$$PH_2 = 0.5P_{H_2o}^{sat}\left[\frac{1}{\exp\left(\frac{1.635\left(\frac{i}{A}\right)}{T^{1.334}}\right)\cdot\left(\frac{P_{H_2o}^{sat}}{P_a}\right)} - 1\right] \tag{4}$$

Where, P_a and P_c are the anode and cathode inlet pressure in atmospheres, A is the effective electrode area in Cm^2, i is the current of each cell in amperes, $P_{H_2o}^{sat}$ is the amount of saturated steam pressure that its value depends on the fuel cell. $P_{N_2}^{channel}$ is the partial pressure of N_2 in the cathode gas flow channels in atmospheres which can be calculated by the following equation.

$$P_{N_2}^{channel} = \frac{0.79}{0.21} PO_2 \quad (5)$$

All amounts used in this article, are the same data available in the reference (Zhigun et al., 2005).

Genetic algorithm introduction

Genetic algorithms (GAs) are stochastic optimization techniques founded on the concepts of natural selection and genetics. The algorithm starts with a set of solutions called population. Solutions from a population of chromosomes are used to form a new population. Once the initial population is formed, the GA creates the next generation using three main operators: (1) reproduction, (2) crossover and (3) mutation. Reproduction is the process in which the most fits chromosomes in the population receives correspondingly large number of copies in the next generation. This operation increases quality of the chromosomes in the next generation and therefore leads to better solutions of the optimization problem. The crossover operator takes two of the selected parent chromosomes and swaps parts of them at a randomly selected location. This provides a mechanism for the chromosomes to mix and match their desirable qualities in forming offspring. Mutation plays a secondary role in the GA to alter the value of a gene at a random position on the chromosome string, discovering new genetic material or restoring last material. New solutions are selected according to their fitness: the more suitable they are, the more chances they have to reproduce. This produce repeated until some condition is satisfied. With crossover and mutation taking place, there is a high risk that the optimum solution could be lost as there is no guarantee that these operators will preserve the fittest string. To counteract this, elitism mechanism is often used. In this mechanism, the best individual from a population is saved before any of these operations take place. After the new population is formed and evaluated, it is examined to see if this best structure has been preserved. If not, the saved copy is reinserted back into the population. Using selection, crossover, and mutation on their own will generate a large amount of different probable solutions. However, some main problems can arise. Depending on the initial population chosen, there may not be enough diversity in the initial solutions to ensure the GA searches the entire problem space. Furthermore, the GA may converge on sub-optimum solutions due to a bad choice of initial population. Moreover, inappropriate operator rates can destroy good solutions and degenerate the GA into a random search. These problems may be overcome by the introduction of an improvement mechanism into the GA (Pham and Karaboga, 2000). In solving an optimization problem, its optimization parameters are considered. At first, some general points within the range which are called population are selected randomly, and then these points are coded. Usually the code boxes are formed by from 0 and 1. Figure 2 displays optimal solution by genetic algorithm for a hypothetical problem in which the population consists of four code box. These boxes are called chromosomes. Each chromosome is a volunteer to solve the optimum value. Chromosome growth should be in the direction that results in an optimal solution for the problem. For the next chromosomes producing, each chromosome is evaluated in the function value. Each of these chromosomes which have higher function values is more valuable. The probability of each chromosome selected for reproduction depends on the function value. For example, in Figure 2, function value of each chromosome is equal to the number of 1s in the box. For each pair of parents from selective chromosomes, two infants are created by basic operator namely crossover (Haupt and Haupt, 2004). Crossovers from single-point are different from the other crossovers. In a single- point crossovers, a crossover point is selected randomly, then from the starting point, binary codes to the crossover point are carried from parent to parent and vice versa (Figure 2). And in the next step (that is, Mutation) a bit of chromosome is reversed. Then these processes continue and optimization is done.

Using genetic algorithms (GA) to tuning controller parameters

With so much development in controlling systems and making applicable of these controllers, in power system, simple controllers are still considered desirable controllers (Pham and Karaboga, 2000). In most cases in the power systems, compensators are Lead-Lag controllers. And these controllers can be implemented easily in analog and digital systems. In this paper, Lead-Lag controller is used to control voltage of proton exchange membrane fuel cell. The overall controller schematic is shown in Figure 3.

Controller general form is expressed in Equation 6. The controller parameters must be optimized include: k_p, T_1, T_2. It is clear that the transient mode of the system in the load variations depends on the controller coefficients. Controller design methods are not viable to be implemented because this system is an absolute

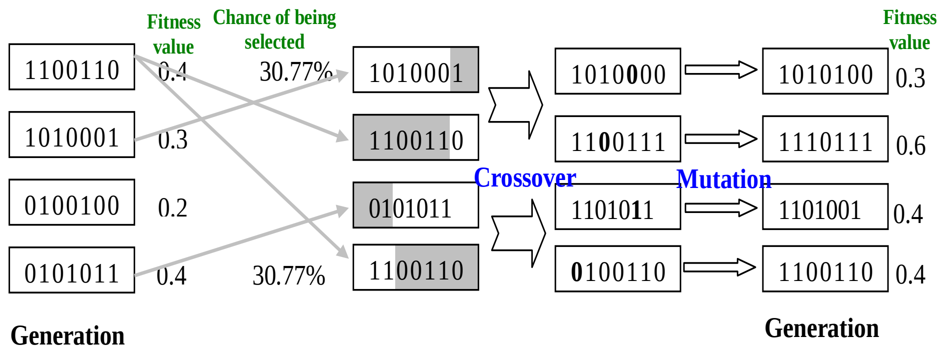

Figure 2. Schematic representation of genetic algorithm for an assumptive optimization.

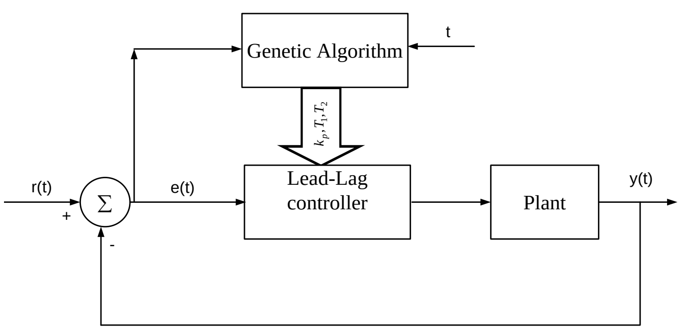

Figure 3. The proposed controller structure.

nonlinear system. So these methods would have not efficient performance in the system.

$$G_c(s) = k_p \frac{1+sT_1}{1+sT_2} \tag{6}$$

In order to design controller using genetic algorithm for the fuel cell from the load current curve, we consider the worst condition for load design controllers for these conditions. Figure 4 displays the worst condition for load current in the system for voltage equal to 20 v.

Now, problem should be written as an optimization problem and then be solved. Selecting objective function is the most important part of this optimization problem. Because, choosing different objective functions may completely change the particles variation state. In optimization problem here, we use error signal:

$$J = \int_0^{t=tsim} \left| v_{out} - v_{ref} \right| dt \tag{7}$$

Where, Tsim is the simulation time in which objective function is calculated. We are reminded that whatever the objective function is a small amount in this case the answer will be more optimized. Each optimizing problem is optimized under a number of constraints. At this problem constraints should be expressed as:

$$\begin{aligned} &Minimize\ J\ subject\ to \\ &k_p^{\min} \le k_p \le k_p^{\max} \\ &T_1^{\min} \le T_1 \le T_1^{\max} \\ &T_2^{\min} \le T_2 \le T_2^{\max} \end{aligned} \tag{8}$$

Where, T_1, T_2 are in the interval [0.01 50] and k_p in the interval [100,800].

In this problem, the number of particles, dimension of the particles, and the number of repetitions are selected, that is, 40, 3 and 50, respectively. After optimization, results are determined as:

$$k_p = 154.25\ , T_1 = 0.13366, T_2 = 0.35014 \tag{9}$$

SIMULATION RESULTS

To show good performance of the proposed algorithm, we consider variable load for fuel cell. Desired load current is shown in Figure 5. In Figure 6, the amount of fuel cell power demand or load power variation is displayed. Desired load is considered under the constant output voltage, while the current is changing between the range of 10 to 15 A, and the number of its changes is considered more to show the performance of the proposed controller.

Simulation output results obtained from the proposed algorithm which is expressed in Equation 9 are shown in Figures 7, 8 and 9. Figure 7 depicted the gas pressure in anode and cathode, load current, output voltage and reference voltage. From this figure, it can be seen that by changing load current; gas pressure in the anode and cathode change quickly to keep stable the output voltage of the fuel cell at the desired voltage and this show good

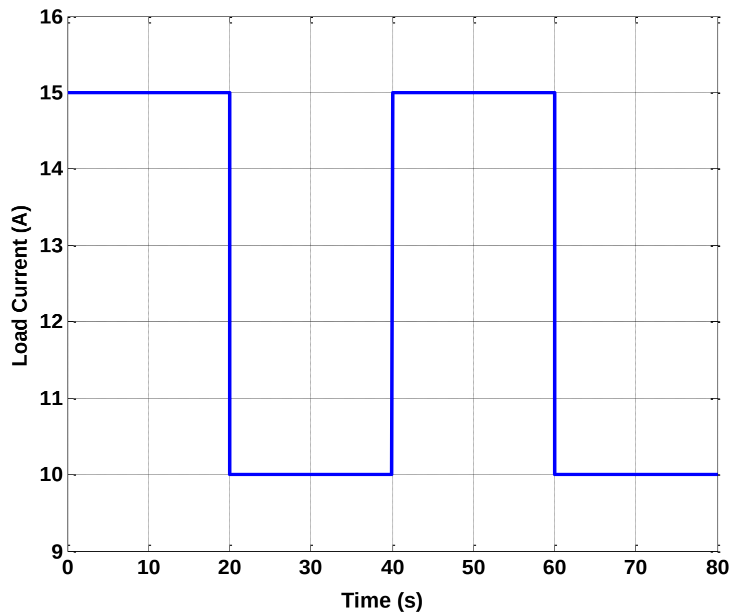

Figure 4. Load current changing in order to solve optimization problem.

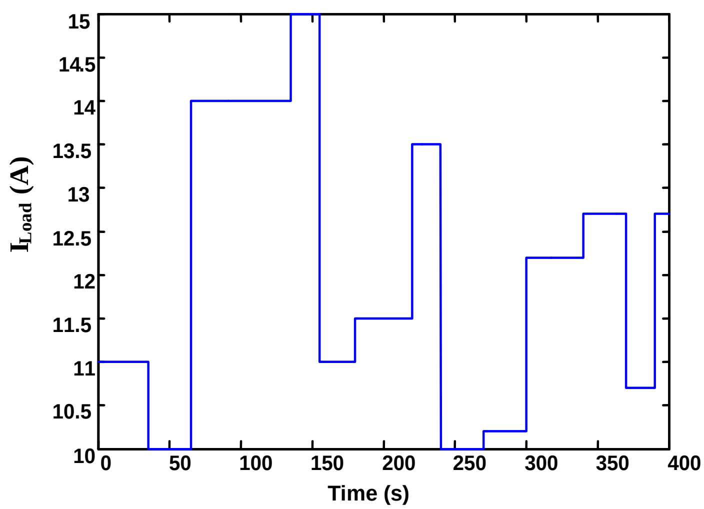

Figure 5. Load current, considering constant voltage for the fuel cell.

performance of the proposed controller albeit simplicity. In Figure 8, output voltage of load and reference voltage are shown, according to the figure, it is obvious that controller response is appropriate and it could follow the reference voltage properly. In Figure 9, the error of the output voltage to the reference voltage is plotted, which the high efficiency of the proposed algorithm shown clearly.

Conclusion

In this paper, a new controller based on genetic algorithms and Lead-Lag controller to control the fuel cell output voltage was proposed. This controller is chosen because of its simplicity and because it could obviate the problem of the previous controller and its efficiency is higher than previous controllers. GA algorithm was utilized to design the Lead-Lag controller to have the most optimized state. In solving this problem, at first problem was written in the form of the optimization problem which its objective function was defined and written in time domain and then the problem has been solved using genetic algorithm. And the most optimal mode for gain coefficient and controller zero and pole were determined using the algorithm.

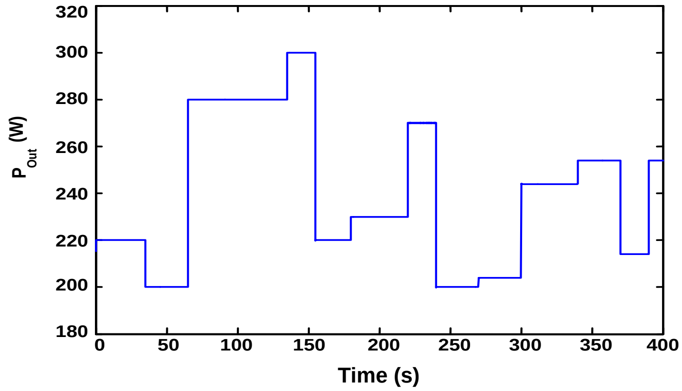

Figure 6. Power demand from the fuel cell.

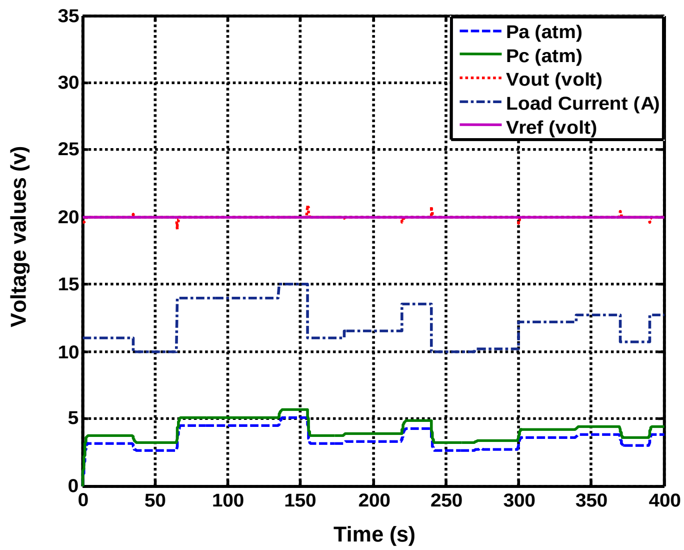

Figure 7. Anode and cathode gas pressure, the system load, output voltage and reference voltage related to the proposed controller.

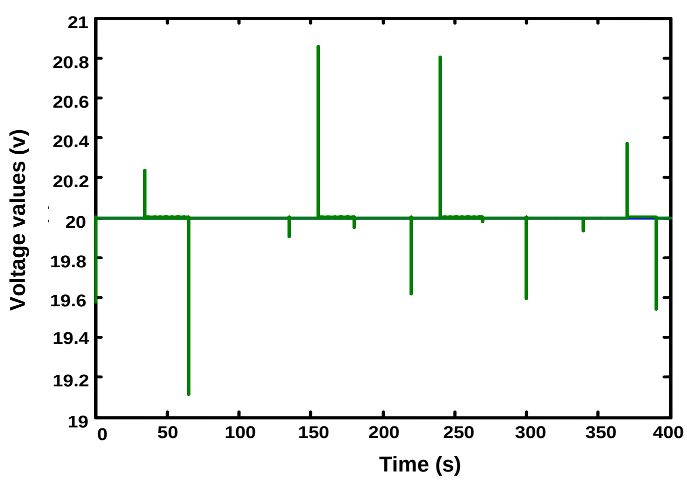

Figure 8. Fuel cell output voltage related to the proposed controller.

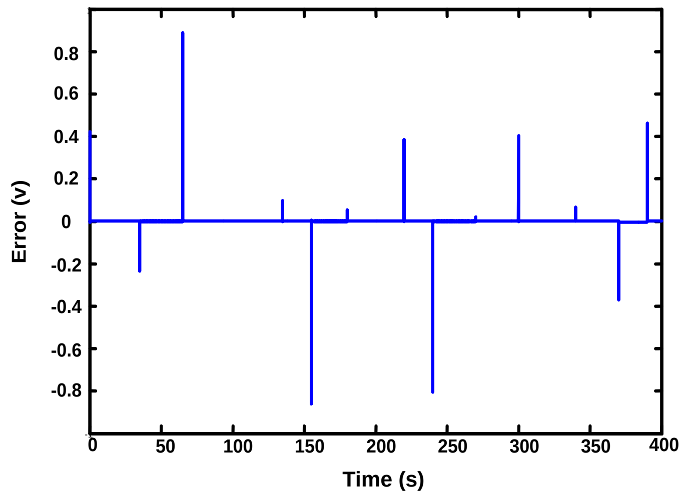

Figure 9. Difference between the output voltage and the reference voltage related to the proposed controller.

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