Int. J. Electrochem. Sci., 7 **(2012)** 6426 - 6435

International Journal of
ELECTROCHEMICAL
SCIENCE
www.electrochemsci.org

Technical Report

Using Tournament Selection Approach to Improve Harmony Search Algorithm for Modeling of Proton Exchange Membrane Fuel Cell

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Received: 24 February 2012 / *Accepted:* 2 June 2012 / *Published:* 1 July 2012

In this paper, a tournament selection-based harmony search algorithm, named TSHS, is developed to identify the parameters of a proton exchange membrane fuel cell (PEMFC) model. In the proposed algorithm, the performance of the original harmony search (HS) algorithm to improvise a new harmony is improved. To assess the optimization power of TSHS, its performance is compared with that of two versions of HS algorithms and two versions of particle swarm optimization (PSO) algorithms. Simulation results reveal that TSHS algorithm has a better performance than the other investigated methods.

Keywords: Proton exchange membrane fuel cell, Polarization curve, Modeling, Tournament selection-based harmony search algorithm

1. INTRODUCTION

Environmental problems resulted from the use of fossil fuels, along the years, are the major reason of creating a steadily increasing demand towards generating electrical energy with dirt-free conversion technologies. Fuel cells (FCs) are electrochemical devices which are known one of the most popular kinds of new technologies for their low aggression to the environment, high efficiency, good dynamic response, and low noise. They can provide electrical energy for various applications like transportation, stationary and portable power generation systems [1].

Depending the type of electrolyte materials, there are different kinds of FCs. Because of its promising features, proton exchange membrane fuel cell (PEMFC) has attracted significant interest among FCs. It operates at a relatively low operating temperature allowing a fast start-up, uses a solid

polymer electrolyte reducing the problems related to construction and safety, and has high current density.

Polarization curve, representing the voltage vs. current (*V-I*), is one of the most important characteristics of FCs. Optimization of FC operating points, design of power conditioning units, design of simulators for FC stack systems, and design of system controllers depend on such characteristic [2,3]. Thus, there is a need to model polarization curve.

Although to predict the performance of a PEMFC many models have been developed in the literature [4], but the level of complexity associated with these models varies considerably. However, models appropriate for engineering aims and easy to solve are rarely available. During modeling the electrochemical and/or thermodynamic phenomena inside PEMFC are expressed by different formulas. Model formulas include a set of unknown parameters that are functions of the operating conditions. As a result, in order to achieve exact simulation results for a given set of operating conditions a corresponding set of parameters is needed. This means that model equations will produce wrong results if constant values for parameters are used in the whole period that a PEMFC is working. To overcome this problem parameter identification is indispensable.

Because of the inherent non-linearity and complexity of polarization curve, traditional optimization methods may easily get stuck in local minima [5]. So, some researchers have tried to apply heuristic optimization algorithms such as genetic algorithm (GA) [6,7,8], particle swarm optimization (PSO) [9,10], and simulated annealing (SA) [11]. Though these algorithms have better performance than traditional methods, but they have their deficiencies [12] and a better optimization technique is needed.

Inspired from musician's improvisation process, harmony search (HS) [13] is an evolutionary algorithm which attempts to imitate the search process of musicians for finding a perfect state of harmony. It has simple concept, uses no derivative information, imposes a small number of requirements, and can be simply adopted for using in optimization problems [14]. These merits make HS as one of serious opponents of other evolutionary algorithms.

In this paper, to improve the performance of HS algorithm, a tournament selection-based HS algorithm, named TSHS, is proposed to identify the parameters of a PEMFC's polarization curve model. In TSHS the selection approach of a harmony from harmony memory (HM) to improvise a new harmony is improved. In order to observe the performance of TSHS, the results are compared with two versions of HS algorithms and two versions of particle swarm optimization (PSO) algorithms.

The organization of this paper is as follows. In the next section parameter identification problem is defined. Section 3 introduces HS algorithm. In section 4 the proposed TSHS is described in detail. Simulation results are discussed in section 5. Finally, conclusion is drawn in section 6.

2. DEFINITION OF PROBLEM

When current is drawn from a fuel cell, the cell voltage falls due to polarization. The higher the current, the greater the voltage drop is. The polarization curve indicates the cell voltage as a function of current.

2.1. Modeling of Polarization Curve

When current is drawn from a fuel cell, the cell voltage falls due to polarization. The higher the current, the greater the voltage drop is. The polarization curve indicates the cell voltage as a function of current. There are three kinds of voltage drops affecting the overall cell voltage: activation voltage drop, ohmic loss, and concentration voltage drop. Activation voltage drop is caused by the slowness of the reactions which take place on the surface of electrodes. Accordingly, a portion of generated voltage is lost in driving the chemical reaction that transfers the electrons to or from the electrode. This voltage drop is extremely non-linear and more significant in low currents. Ohmic loss which is linearly proportional to cell current occurs in the electrolyte and electrodes. However, this loss is expressed by Ohm's law. Concentration voltage drop results from the effect of mass transport on the concentration of hydrogen and oxygen. This voltage drop is more significant at high cell currents. The polarization curve model of a PEMFC can be represented by the following expression [7,15]:

$$\begin{aligned} V &= n\times[E_{Nernst} - V_{act} - V_{ohmic} - V_{con}] \\ &= n\times[\{1.229 - 0.85\times10^{-3}(T - 298.15) \\ &+ 4.31\times10^{-5}T\times(\ln(P_{H_2}P_{O_2}^{0.5}))\} \\ &+ \{\xi_1 + \xi_2 T + \xi_3 T\ln(C_{O_2}) + \xi_4 T\ln(i)\} \\ &- \{i(R_M + R_C)\} + \{b\ln(1 - J/J_{\max})\}] \end{aligned} \quad (1)$$

where E_{Nernst}, V_{act}, V_{ohmic}, and V_{con} are, respectively, the cell reversible voltage, activation voltage drop, ohmic loss, and concentration voltage drop, n is the number of fuel cells in series, T denotes the cell temperature, P_{H2} and P_{O2} are the partial pressures of hydrogen and oxygen, respectively, C_{O2} is the oxygen concentration at the cathode, i shows the cell current, ξ_i are parametric coefficients, R_M and R_C are, respectively, the equivalent membrane resistance to proton conduction and equivalent contact resistance to electron conduction, b is a parametric coefficient, and J and J_{max} are the actual and maximum current density, respectively.

In Eq. (1) C_{O2} and R_M are obtained by Eq. (2) and Eq. (3), respectively.

$$C_{O2} = \frac{P_{O_2}}{5.08\times10^6\times e^{-498/T}} \quad (2)$$

$$R_M = \rho_M \cdot l/A \quad (3)$$

where l denotes the membrane thickness, A is the cell active area, and ρ_M indicates the specific resistivity of the membrane expressed by following formula [13]:

$$\rho_M = \frac{181.6[1 + 0.03(i/A) + 0.062(T/303)^2(i/A)^{2.5}]}{[\lambda - 0.634 - 3(i/A)]\times e^{[4.18(\frac{T-303}{T})]}} \quad (4)$$

where λ is the water content of the membrane.

There are other causes for voltage drop in fuel cells due to fuel crossover and internal currents. Though the electrolyte is constructed that only the ions can pass through it, but a definite quantity of fuel and electron are conducted through the electrolyte. This phenomenon leads to an energy loss and is included to model by adding a parameter J_n to the actual current density [17].

2.2. The Objective Function

The unknown parameters of the model are A, l, R_C, ξ_1, ξ_2, ξ_3, ξ_4, J_n, J_{max}, λ, and b. Among these parameters A and l are dimensional parameters obtainable of manufacture's data sheet. Therefore, the identification problem reduces to extract the value of nine parameters namely R_C, ξ_1, ξ_2, ξ_3, ξ_4, J_n, J_{max}, λ, and b. In the model the partial pressures and concentrations are constant.

In order to carry out the identification process an objective function must be first defined. The objective function value influences on how to perform the identification of the PEMFC model parameters. For fitting the results obtained from the model over a set of experimental data, the objective function is defined by the following formula:

$$OF = \sqrt{\frac{1}{Q}\sum_{q=1}^{Q}\left(U_q - V_q\right)^2} \qquad (5)$$

where U_q is the experimental data, V_q is the simulated data from the model, and Q is number of the experimental data.

In order to achieve this purpose, the model parameters are successively adjusted by the optimization algorithm until a predefined criterion is satisfied. In this case, the smaller value of the objective function, the better the solution is.

3. HARMONY SEARCH (SH) ALGORITHM

HS algorithm, devised in an analogy with music improvisation process where musicians improvise the notes of their instruments to achieve better harmony, is a high-performance meta-heuristic algorithm which uses stochastic random search instead of a gradient search. This algorithm has been successfully applied to various optimization problems [18-20].

In order to find a perfect state of harmony, a musician improvises a number of notes. To improvise a note he (or she) employs one of three rules: (1) a random note from possible range (2) a note from harmony memory (HM) (3) a note close to one of the HM's notes. The quality of new harmony is measured by aesthetic standard.

On the other hand, the main goal of optimization methods is minimization or maximization of the function under consideration by finding a group of decision variables which make a vector together. The quality of each vector is determined via its objective function value. Finding global

optimum is the ultimate goal of an optimization technique. The HS algorithm tries to mimic the musician improvisation process for solving optimization problems. Therefore, in HS algorithm decision variable, vector, and objective function correspond with note, harmony, and aesthetic standard, respectively.

HS algorithm has a harmony memory (HM) which is initialized at the beginning of the algorithm with a group of feasible solutions for the problem on the hand. HM is a $HMS \times d$ matrix which *HMS* is the harmony memory size (number of memory harmonies) and *d* denotes the problem dimension (number of decision variables).

Three HS parameters which have a great influence on the convergence rate of the algorithm are harmony memory considering rate (*HMCR*), pitch adjusting rate (*PAR*), and bandwidth of generation (*bw*). The *HMCR* is rate of choosing one value from the HM and varies between 0 and 1. *PAR* and *bw* are defined by the following formulas [14]:

$$PAR(t) = PAR_{\min} + \frac{PAR_{\max} - PAR_{\min}}{t_{\max}} \times t \tag{6}$$

$$bw(t) = bw_{\max} \exp(c \cdot t) \tag{7}$$

$$c = \frac{Ln(bw_{\min} / bw_{\max})}{t_{\max}} \tag{8}$$

where PAR_{max} and PAR_{min} are the maximum and minimum pitch adjusting rates, respectively, *t* denotes the iteration index, t_{max} is the maximum number of iterations, and bw_{max} and bw_{min} are, respectively, the maximum and minimum bandwidths.

In this paper, a harmony is considered by vector $x = [R_C\ \xi_1\ \xi_2\ \xi_3\ \xi_4\ J_n\ J_{max}\ \lambda\ b]$ to denote a feasible set of parameters of the model. The steps of HS algorithm are as follows:

Step 1: the values of *HMS*, PAR_{max}, PAR_{min}, bw_{max}, bw_{min} , and t_{max} are assigned.

Step 2: the HM is initialized with a group of feasible random harmonies with the following expression:

$$x_i(j) = l(j) + \alpha \times (u(j) - l(j)) \tag{9}$$

where $i=1,2,\ldots,HMS$ is harmony's index, $j=1,2,\ldots,d$ denotes the decision variable's index, α is a random number uniformly from the interval [0, 1], and $l(j)$ and $u(j)$ are the lower and upper bounds of j^{th} decision variable, respectively.

Step 3: the value of objective function for each harmony in HM is computed using Eq. (5).

Step 4: a new harmony is improvised as follows.

```
for j = 1:d
    if r1 ≥ HMCR
        x_new(j) = l(j) + r2 × (u(j) − l(j));
    else
        select randomly one of HM harmonies (x_r)
        x_new(j) = x_r(j);
        if r3 < PAR
            x_new(j) = x_new(j) + (r4 − r5) × bw × |u(j) − l(j)|;
        end
    end
end
```

where r_1, r_2, r_3, r_4, and r_5 are random numbers from the interval [0, 1].

Step 5: the new harmony is checked to see whether it is in the search space. If it is in the search space the next step is performed, otherwise, the step 4 is performed.

Step 6: the new harmony is included to the HM and the worst HM's harmony is excluded if the quality of the new harmony is better than that of the worst harmony of HM.

Step 7: step 4 to step 6 are repeated until the maximum iteration times are reached.

4. TOURNAMENT SELECTION-BASED HS ALGORITHM

In the improvisation stage of HS algorithm, there is no way to control the quality of harmony selected from HM; accordingly, any harmony of HM can be a nominee. However, this way may have a bad effect on the HS performance. In [21] authors have used from the best harmony of HM to improvise a new harmony. However, this way may be influenced by premature convergence because the best harmony may be a local optimum and the algorithm cannot get out of it. In order to provide an effective way to select a note from HM two aspects must be considered. From the standpoint of the first aspect use of good harmonies for improvisation process increases the probability of generating a new harmony with better quality. The second aspect takes into account the fact that harmonies with worse qualities may include some information which the algorithm can be easily converged to global optimum. As a result, an efficient HS algorithm must be able to provide a way with which the improvisation process can be truly accomplished.

In this paper, a tournament selection-based harmony search algorithm, named TSHS, is proposed. In TSHS a predetermined number of HM harmonies participate in a tournament and the winner of the tournament *win* (one with the best quality), is selected as interesting harmony for improvisation. In tournament selection approach, harmonies with better qualities have a more chance of being selected. However, the selection pressure is easily adjusted by tournament size t_s.

The tournament participants t_p, are randomly selected using the following formula:

$$t_p = ceil\left(HMS \times rand\left(1, t_s\right)\right) \tag{10}$$

where *rand* generates a random vector drawn from a uniform distribution on the unit interval in which its length is t_s and *ceil* rounds it toward infinity.

The steps of the TSHS are same as those of HS just the step 4 is replaced as follows.

$$
\begin{aligned}
&for\ j = 1:d \\
&\quad if\ r_1 \geq HMCR \\
&\qquad x_{new}(j) = l(j) + r_2 \times (u(j) - l(j)); \\
&\quad else \\
&\quad select\ tornament\ participats \\
&\quad perform\ a\ tornament\ between\ participats \\
&\quad select\ the\ winner\ of\ the\ tournament\ (win) \\
&\quad x_{new}(j) = win(j) \\
&\quad if\ r_3 < PAR \\
&\qquad x_{new}(j) = x_{new}(j) + (r_4 - r_5) \times bw \times |u(j) - l(j)|; \\
&\quad end \\
&end \\
&end
\end{aligned}
$$

5. RESULTS AND DISCUSSION

In our study, the proposed TSHS algorithm is coded and executed in the Matlab software to identify the unknown parameters of one single cell, the Ballard Mark V FC (T = 343 K, A = 50.6 cm^2, l = 178 μm, P_{H2} = 1 atm, and P_{O2} = 1 atm) [22]. After providing a literature survey [7,16,22,23], the range of parameters is shown in table 1.

Table 1. The range of the model parameters

Parameter	Max	Min
R_C (Ω)	0.0008	0.0001
ξ_1	-0.8532	-1.1997
ξ_2	0.005	0.001
ξ_3	9.8×10^{-5}	3.6×10^{-5}
ξ_4	-0.954×10^{-4}	-2.6×10^{-4}
J_n (mA cm^{-2})	30	1
J_{max} (mA cm^{-2})	1500	500
λ	24	10
b (V)	0.5	0.0136

The performance of TSHS algorithm (TSHS: $HMCR$ = 0.95, PAR_{max} = 1, PAR_{min} = 0.3, bw_{max} = 1, bw_{min} = 0.001) is compared with improved HS (IHS: $HMCR$ = 0.95, PAR_{max} = 1, PAR_{min} = 0.3, bw_{max} = 1, and bw_{min} = 0.001) [14], self-adaptive global HS (SGHS: $HMCR$ = 0.95, PAR_{max} = 1, PAR_{min} = 0.3, bw_{max} = 1, and bw_{min} = 0.001) [21], PSO with adaptive inertia weight (PSO-w: learning rate c_1 =

c_2 = 2, and inertia weight linearly decreases from 0.9 to 0.4 during run time) [24], and PSO with constriction factor (PSO-cf: c_1 = c_2 = 2.01) [25]. In the all studied algorithms size of population and maximum number of iterations are tuned at 90 and 10000, respectively.

The success of the TSHS algorithm is evaluated in terms of the shape of the fitted polarization characteristic and the value of the objective function. Because of the stochastic essence of the investigated algorithms, the results obtained in one attempt will differ from the results obtained in another attempt. Therefore, the performance analysis of the methods must be statistically based. As a result, each algorithm is run 10 times and in each run the best objective function value is recorded. The best (*best*), the worst (*worst*), the mean (*mean*), and the standard deviation (*std*) of the objective function values are summarized in TABLE 2.

Table 2. Comparison of tshs with other methods in terms of the best, the worst, the mean, and the *std* over 10 runs

Index	TSHS	IHS	SGHS	PSO-w	PSO-cf
best	5.13e-3	5.30e-3	5.25e-3	1.67e-2	1.30e-2
worst	7.77e-3	1.07e-2	1.35e-2	3.30e-2	5.00e-2
mean	6.38e-3	8.02e-3	7.87e-3	2.32e-2	3.19e-2
std	1.22e-3	2.13e-3	2.78e-3	4.77e-3	1.13e-2

As results show, TSHS has the smallest *best*, *worst*, *mean*, and *std* values. This means that the search capacity of TSHS is better than that of the other listed algorithms. In comparison with TSHS, although the *best* values found by IHS and SGHS are acceptable, but the worst values are different from the worst value of TSHS.

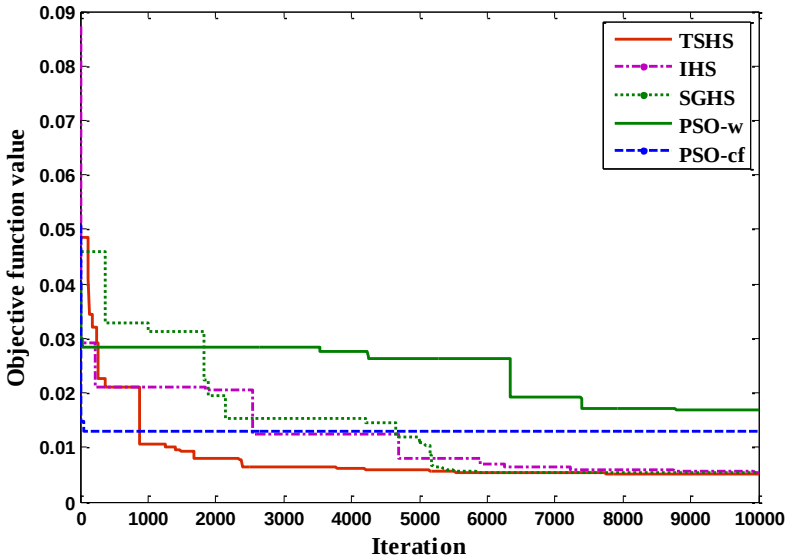

Figure 1. Convergence process of the investigated algorithms

So, it can be drawn that the TSHS has more robust results than IHS and SGHS algorithms. In comparison with HS-based algorithms the performance of PSO-based algorithms is weak, since the *best value* of PSO-based algorithms obtained by PSO-cf is 1.30e-2 while this value is 5.13e-3 for HS-based algorithms which is found by TSHS. Fig. 1 represents the convergence process of the algorithms, which illustrates the best objective function values versus iteration times.

The optimal parameters related to the best performance of the algorithms are listed in TABLE 3. In order to confirm the parameter identification process the optimal parameters found by TSHS are put into the model and polarization curve is plotted. Fig. 2 indicates that the identified model is in good agreement with the experimental data.

Table 3. Model parameters related to the best performance of the algorithms

Parameter	TSHS	IHS	SGHS	PSO-w	PSO-cf
R_C	0.00056	0.00055	0.00023	0.00029	0.00058
ξ_1	-0.9713	-0.9978	-1.1733	-0.9922	-1.0151
ξ_2	0.00347	0.00336	0.00365	0.00337	0.0035
ξ_3	8.33e-5	6.90-5	5.39e-5	7.55e-5	4.06e-5
ξ_4	-1.25e-4	-1.26e-4	-1.32e-4	-0.957e-4	-2.19e-4
J_n	17.06	13.71	7.74	29.56	19.52
J_{max}	1484.51	1481.06	1473.47	810.10	763.82
λ	23.89	22.99	22.62	18.47	16.03
b	0.0204	0.0186	0.0214	0.0136	0.0189

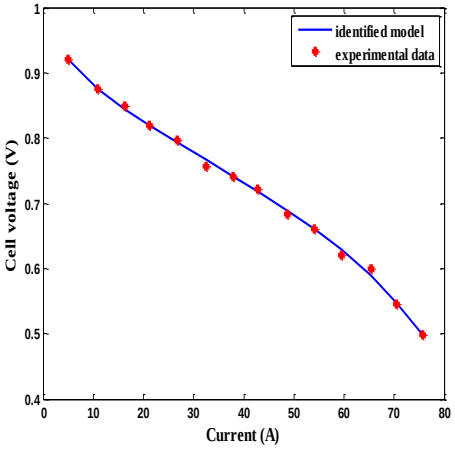

Figure 2. Comparison between the identified polarization curve with the TSHS and the experimental data

6. CONCLUSION

In this paper, a novel harmony search algorithm, named TSHS, is proposed for parameter identification of a PEMFC polarization curve model. The proposed algorithm is a method of

improvement the improvisation stage of HS algorithm, merging the tournament selection approach and harmony search algorithm to increase the search ability of the original HS. The acquired results manifest that the performance of TSHS is better than that of two versions of HS algorithms and two versions of PSO algorithms.

ACKNOWLEDGEMENTS
The financial support of the Renewable Energy Organization of Iran (SANA) is greatly acknowledged.

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