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SPECIAL ISSUE ON GREEN HYDROGEN AND FUEL CELL SYSTEMS

A new heuristic optimization algorithm for modeling of proton exchange membrane fuel cell: bird mating optimizer

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SUMMARY

As an open and demanding problem, accurate modeling of polarization curve in proton exchange membrane fuel cell has become the main issue of various researches. In recent years, because of their great potentials, metaheuristic optimization algorithms have represented good performances in identification of the unknown parameters of the proton exchange membrane fuel cell model, but there is the possibility to obtain more accurate results with more capable algorithms. In the literature, many heuristic optimization algorithms have been developed on the basis of natural phenomena. However, there are still some possibilities to devise new ones. In this paper, evolution of bird species has been regarded, and the intelligent behavior of birds during mating season has become an inspiration to devise a new heuristic optimization algorithm, named bird mating optimizer. Moreover, in this paper, the whole unknown parameters of the model, even dimensional parameters, are included in the identification process. The proposed algorithm is used to model the Ballard Mark V FC, and its performance is compared with those of the recently published paper by the authors. Simulation results reveal the superior performance of bird mating optimizer algorithm. Copyright © 2012 John Wiley & Sons, Ltd.

KEY WORDS

fuel cell; polarization curve; parameter identification; heuristic methods; bird mating optimizer algorithm

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1. INTRODUCTION

Environmental problems that resulted from the use of fossil fuels, along the years, are the major reason for creating a steadily increasing demand towards generating electrical energy with dirt-free conversion technologies. Fuel cells (FCs) are electrochemical devices that are known as one of the most popular kinds of new technologies because of their low aggression to the environment, high efficiency, good dynamic response, and low noise. Because of these multiple advantages, they are the best candidate to provide electrical energy for various fields such as transportation, stationary, and portable applications.

Depending on the type of electrolyte materials, there are different kinds of FCs. Because of its promising features, proton exchange membrane FC (PEMFC) has received significant attention 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 voltage versus current (*V–I*), is one of the most important characteristics of FCs. Optimization of FC operating points, design of power conditioning units, simulators for FC stack systems, and system controllers depend on such characteristic [1]. Thus, there is a need to accurately model polarization curves. Although to predict the performance of a PEMFC, many models have been developed in the literature [2], the level of complexity associated with these models varies considerably. However, models appropriate for engineering aims and easy to solve are rarely available. Modeling the electrochemical and/or thermodynamic phenomena inside a PEMFC is represented by a mathematical model. Model formulas include a set of unknown parameters that are functions of the operating conditions. 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 system is working. To overcome this problem, parameter identification is indispensable.

Because of the inherent nonlinearity and complexity of polarization curve, traditional optimization methods may easily be stuck in local optima. To conquer this drawback, many heuristic algorithms such as genetic algorithm [3,4], particle swarm optimization [5], artificial immune system [6], harmony search (HS) [7], artificial bee swarm optimization [8], and seeker optimization algorithm [9] have been applied. Although in the aforementioned investigations, satisfactory results have been reported, there is the possibility to achieve better results with more capable algorithms. Moreover, the main deficiency of these investigations is that the whole unknown parameters have not been considered during identification process so that either some parameters because of their trivial effects have been neglected or dimensional parameters have been addressed to obtain from manufacture's data sheet. However, some researchers [10] have indicated that no-load current density (J_n), which has been neglected in some investigations, is important, in particular, at the low current densities. On the other hand, some parameters, that is, membrane thickness and cell surface area, are only known for manufacture, and owing to security problems, it may be unable to reveal them. As a result, developing a parameter identification problem that takes into account all the unknown parameters is essential.

Because of the growing complexity of real-world optimization problems, better optimization algorithms are always needed. Most often, heuristic methods have a good performance, but in some cases, the complexity of problems is so high that even existing heuristic methods are unable to achieve satisfactory solution in a reasonable runtime. However, there are still some possibilities to invent new heuristic approaches.

Birds are the most speciose class of tetrapod vertebrates, having around 10,000 living species [11]. They communicate by use of visual and auditory signals. Songs are usually used for many aims such as mate attraction, evaluation of potential mates, bond formation, and the claiming and maintenance of territories. Some birds use their plumages to assess and assert social dominance and to display breeding condition. During the mating season, the main goal of a bird is to raise a brood that can survive longer, so it tries to find mate(s) with good genes. The behavior of courtship in birds is naturally innate. Depending on the bird species, the mating processes are performed by different strategies [11–14]. Generally, there are four strategies: monogamy, polygamy, polyandry, and promiscuity.

The behavior of birds to raise broods with superior genes resembles with optimization process in which finding the global solution (a perfect state) is the ultimate aim. As a result, in this paper, a new optimization algorithm inspired by mating process of bird species is proposed and named bird mating optimizer (BMO). This algorithm is applied to parameter identification of the Ballard Mark V FC. In [7], a grouping-based global HS (GGHS) algorithm has been developed by the authors and used to identify some parameters of the Ballard Mark V FC. GGHS has obtained the best performance among the other investigated heuristic algorithms. In order to assess the optimization power of BMO algorithm, its performance is compared with the performances of GGHS and other HS-based algorithms.

The rest of this paper has been organized as follows: in Section 2, the PEMFC parameter identification problem is explained; the proposed algorithm is described in detail in Section 3; Section 4 explains the use of the proposed algorithm in the parameter identification problem; simulation results and discussions are indicated in Section 5; and finally, conclusion is stated in Section 6.

2. DEFINITION OF THE PROBLEM

2.1. Modeling of polarization curve

When current is drawn from an FC, the cell voltage falls because of 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 electrochemical reactions that take place on the surface of electrodes. Accordingly, a portion of generated voltage is lost in driving the electrochemical reaction that transfers the electrons to or from the electrode. This voltage drop is extremely nonlinear 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 [3,15]:

$$
\begin{aligned}
V &= n \times \left[E_{\mathrm{Nernst}} - V_{\mathrm{act}} - V_{\mathrm{ohmic}} - V_{\mathrm{con}}\right] \\
&= n \times \Big[\Big\{1.229 - 0.85 \times 10^{-3}(T - 298.15) \\
&\quad +4.31 \times 10^{-5} T \times \left(\ln\left(P_{\mathrm{H}_2} P_{\mathrm{O}_2}^{0.5}\right)\right)\Big\} \\
&\quad +\{\xi_1 + \xi_2 T + \xi_3 T \ln(C_{\mathrm{O}_2}) + \xi_4 T \ln(i)\} \\
&\quad -\{i(R_{\mathrm{M}} + R_{\mathrm{C}})\} + \left\{b \ln\left(1 - \frac{J}{J_{\max}}\right)\right\}\Big]
\end{aligned}
\tag{1}
$$

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 FCs in series; T denotes the cell temperature; P_{H_2} and P_{O_2} are the partial pressures of hydrogen and oxygen, respectively; C_{O_2} 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 $J = i/A$ and $J_{\max}$ are the actual and maximum current density, respectively.

In Equation (1) C_{O_2} and R_M are obtained by Equations (2) and (3), respectively.

$$C_{O_2} = \frac{P_{O_2}}{5.08 \times 10^6 \times e^{-498/T}} \tag{2}$$

$$R_M = \frac{\rho_M \cdot l}{A} \tag{3}$$

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 [16]:

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

where λ is the water content of the membrane.

There are other causes of voltage drop in FCs due to fuel crossover and internal currents. Although the electrolyte is constructed that only the ions can pass through it, a definite quantity of fuel and electrons are conducted through the electrolyte. This phenomenon leads to an energy loss and is included to the 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. 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:

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

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

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 the value of the objective function, the better the solution is.

3. BIRD MATING OPTIMIZER ALGORITHM

Evolution process among bird species can be an inspiration to devise a new heuristic optimization algorithm. In this paper, a new BMO algorithm is conceptualized using the mating process of bird for raising a superior brood (a perfect state). During mating season, birds employ a variety of intelligent behaviors such as singing, tail drumming, or dancing to attract potential mates. Some courtship rituals are quite elaborate and serve to form a bond between the potential mates. The quality of each brood is specified by its characteristics such as beak, tail, wing, and so on, because by the optimal characteristics, the bird can better fly and catch more food to survive better. The related gene of each characteristic determines the quality of that characteristic, together making the overall quality of the bird. A gene is a hereditary unit that can be passed on through breeding to next generations. Imagine a bird that has good genes among a species. This bird can get more food. Hence, it is healthier than the other birds, lives longer, and breeds more. The bird passes these genes for better ones on to its broods. They also live longer and have more broods, and the gene continues to be inherited generation after generation.

In the same way, an optimization process searches to discover a global solution (a perfect state) in which the quality of each solution is determined by a criterion named objective (fitness) function. In engineering optimization, decision variables are given values in the search space, and a solution vector is made. If a good solution is acquired, that experience is memorized, and the possibility of making a better solution increases at the next time.

With these similarities, an optimization technique can be developed by imitating the mating process of birds. In the proposed algorithm, each bird in the swarm is a feasible solution of the problem and is specified by a predefined number of genes, equal to the problem dimension (number of decision variables). In each generation, the bird attempts to make one brood with better genes by selecting dominant mate(s). The bird during each generation in addition to its mating process and raising one brood may be selected as the mate of the other birds. However, after each generation of the swarm, the number of the raised broods is equal to the swarm population.

According to the bird species, there are different ways to perform mating process. Most birds are monogamous, meaning that a male bird only mates with a female one. During the breeding season a monogamous bird starts to sing. Females receive his song and gather at the vicinity of him. Each female tries to attract the monogamous bird towards herself by dancing. Females with better qualities are more attractive than others and have a more chance of being selected. The male evaluates the qualities of the females, employs a probabilistic approach to select one of them as his attractive female, and mates with her. Mathematically, in BMO algorithm, each gene of the resultant brood obtained by mating the ith monogamous bird and his attractive female can be obtained by the following expression:

$$x_{ij}^{brood} = x_{ij}^{mon} + w \times r \times \left(x_j^{af} - x_{ij}^{mon}\right), \tag{6}$$
$$i = 1, 2, \mathrm{K}, n_{mon}; j = 1, 2, \mathrm{K}, d$$

where x^{brood} is the brood, x^{mon} denotes the monogamous bird, x^{af} is the attractive female, n_{mon} is the number of monogamous birds, d is the problem dimension, r is a random number between 0 and 1, and w is inertia weight, which controls the importance of the attractive female.

In polygamy behavior, a single male mates with multiple females. This behavior usually entails fierce competition between the males during breeding season. When females receive the song of a polygamous bird, gather around him, and start to dance to attract him towards themselves, the polygamous bird probabilistically selects his favorite females and mates with them. Mathematically, in BMO algorithm, each gene of the resultant brood is given using the following expression:

$$x_{ij}^{\text{brood}} = x_{ij}^{\text{polyg}} + w \times \sum_{k=1}^{n_{ff}} r_k \times \left(x_j^{\text{ff}_k} - x_{ij}^{\text{polyg}}\right), \quad (7)$$
$$i = 1, 2, \text{K}, n_{\text{polyg}}; j = 1, 2, \text{K}, d$$

where x^{polyg} denotes a polygynous bird, x^{ff_k} is the kth favorite female, n_{ff} is the number of favorite females, n_{polyg} is the number of polygynous birds, and r_k are random numbers between 0 and 1.

In polyandry behavior, a single female mates with multiple males. During breeding season, a polyandrous bird flaunts her plumages to display her breeding condition. This behavior makes males be aware of the intention of the female, and they gather around her. The males start to sing and try to attract the polyandrous bird towards themselves. Accordingly, each polyandrous bird probabilistically makes a decision, selects her favorite males, and mates with them. Mathematically, in BMO algorithm, each gene of the resultant brood is generated using the following expression:

$$x_{ij}^{\text{brood}} = x_{ij}^{\text{polya}} + w \times \sum_{k=1}^{n_{\text{fm}}} r_k \times \left(x_j^{\text{fm}_k} - x_{ij}^{\text{polya}}\right), \quad (8)$$
$$i = 1, 2, \text{K}, n_{\text{polya}}; j = 1, 2, \text{K}, d$$

where x^{polya} denotes a polyandrous bird, x^{fm_k} is the kth favorite male, n_{fm} is the number of favorite males, n_{polya} is the number of polyandrous birds, and r_k are random numbers between 0 and 1.

Promiscuity is another mating strategy employed by a few bird species, meaning mating systems with no stable relationships in which mating between two birds is a one-time event. This type of mating indicates a rather chaotic social structure in which the male will almost certainly never see his brood or the nest and most likely will not see the female for another brief visit. In BMO algorithm, promiscuous birds are generated using a chaotic sequence. With different qualities, they attend during breeding season to perform mating process. The behavior of promiscuous birds is the same as that of the monogamous birds. Each bird selects his attractive female and mates with her. Mathematically, in BMO algorithm, each gene of the resultant brood is generated using the following expression:

$$x_{ij}^{\text{brood}} = x_{ij}^{\text{pro}} + w \times r \times \left(x_j^{\text{af}} - x_{ij}^{\text{pro}}\right), \quad (9)$$
$$i = 1, 2, \text{K}, n_{\text{pro}}; j = 1, 2, \text{K}, d$$

where x^{pro} denotes a promiscuous bird, n_{pro} is the number of promiscuous birds, and r is a random number between 0 and 1.

4. USING BIRD MATING OPTIMIZER ALGORITHM FOR PARAMETER IDENTIFICATION

As previously mentioned, BMO algorithm employs four types of birds—monogamous, polygamous, polyandrous, and promiscuous—by using different mating strategies to discover the optimum solution in a d-dimensional search space S. Depending on its species, each bird employs a specific way to mate given in the previous section. Using distinct mating patterns increases the flexibility of the algorithm to establish a powerful way to effectively probe the search space.

In the breeding season, a swarm of birds participate in the mating process to raise broods with superior genes. Each bird is specified by a vector $\bar{x}$, representing a feasible solution in the search space so that the jth gene of ith bird is given by x_{ij}. Each gene denotes an unknown parameter of the PEMFC model. At the beginning of the algorithm, the swarm is initialized by the following expression:

$$x_{ij} = l_j + r \times \left(u_j - l_j\right), \qquad i = 1, 2, \text{K}, n \ ; \quad (10)$$
$$j = 1, 2, \text{K}, d$$

where i denotes the bird's index, n is the swarm population, j denotes the gene's index, d specifies the problem dimension, r is a random number in the range of [0, 1], and l_j and u_j are lower and upper bounds of the jth variable.

After initialization of the swarm, the quality of each bird is determined by calculating its objective function value. Thereafter, the species of each bird, determining its mating strategy, must be specified. The bird's quality will specify the mating strategy. Therefore, the birds are sorted according to their qualities and are partitioned into four categories with predefined percentages of the swarm. The birds included in the first category, having the best quality, are considered as females, and the other ones are regarded as males. The females make polyandrous birds. The birds of the second category are selected as monogamous, which have better quality than polygynous birds included in the third category. Polygyny is much more common than polyandry among bird species. The birds of the fourth category are removed, and new ones are generated using a chaotic sequence. The new birds are considered as promiscuous birds.

As an efficient probabilistic approach for monogamous birds to select their attractive females, we resort to roulette wheel. In this approach, the birds with better quality have a great chance of being selected.

A polygynous bird mates with a female by use of an annealing function with the following probability:

$$Pr = \exp\left(-\frac{\Delta f}{tem}\right) \tag{11}$$

where Pr is the probability of mating, Δf denotes the absolute difference between the objective functions of the polygynous bird and female one, and *tem* is an adjustable parameter to control the probability. The probability of mating is high when the quality of the polygynous bird is as good as the favorite female's quality or when the value of *tem* is high. However, a random number between 0 and 1 is generated and compared with the calculated probability. If it is less than the calculated probability, that female bird is selected for mating. Otherwise, the selection of that female is failed.

Polyandrous birds use the annealing function to select their males, too. However, in order to increase the probability of raising a good brood, a predefined percentage of monogamous birds with better quality participates in this rituals.

The chaotic sequence is generated by the well-known logistic function with the following formula:

$$z^{k+1} = 4z^k\left(1 - z^k\right) \tag{12}$$

where z is referred to as chaotic variable and $k = 1, 2, \ldots, iter_{\max}$. At the beginning of the algorithm, to generate a promiscuous bird, d chaos variables, $z_j^0 (j = 1, 2, \ldots, d)$, are initialized with different values between 0 and 1 (not the fixed points of logistic map, i.e., 0.25, 0.5, and 0.75). Then, design variables are calculated by a linear mapping as follows:

$$x_j^{k+1} = l_j + z_j^{k+1}\left(u_j - l_j\right) \tag{13}$$

In BMO algorithm, the inertia weight dynamically decreases during iteration index as the following formula:

$$w = w_{\max} - \frac{w_{\max} - w_{\min}}{iter_{\max}} \times iter, \quad iter = 0, 1, \mathrm{K}, iter_{\max} \tag{14}$$

where $iter$ is the iteration index, $iter_{\max}$ denotes the maximum number of iterations, and $w_{\max}$ and $w_{\min}$ are the maximum and minimum inertia weights, respectively.

At the end of the mating process of all the species, replacement stage is performed. In this stage, the quality of a raised brood is compared with that of the bird that has proceeded to mate. If the brood has a better quality, the bird is removed and the brood is replaced; otherwise, it will be killed. During the replacement stage, if it is found that a brood has left the search space, it will be killed. The mating process will continue until a predefined number of iterations, $iter_{\max}$, is met. The flowchart of the proposed algorithm has been depicted in Figure 1.

5. RESULTS AND DISCUSSIONS

In order to evaluate the optimization ability of BMO algorithm, one single cell, the Ballard Mark V FC ($T = 343$ K, $P_{H_2} = 1$ atm, and $P_{O_2} = 1$ atm), adopted from [18], is regarded. Identification process is used to extract the parameters A, l, R_C, ξ_1, ξ_2, ξ_3, ξ_4, J_n, $J_{\max}$, λ, and b, which are unknown. Table I gives the upper and lower bounds of the parameters, provided by the literature survey [3,16–18].

The performance of the proposed algorithm (BMO: the percentage of monogamous birds is 50% of the swarm, the percentage of polygamous birds is 30% of the swarm, the percentage of polyandrous birds is 10% of the swarm, the percentage of promiscuous birds is 10% of the swarm, the number of monogamous birds participated in mating process of polyandrous birds is 10, $w_{\max} = 2.5$, $w_{\min} = 0.5$, and *tem* is calculated by $tem = -\Delta f_0/\ln(\chi_0)$, where $\chi_0 = 0.2$ is the acceptance rate for the initial worse solution and Δf_0 is the initial difference between the worst and the optimal solution [19]) is compared with the performance of GGHS ($HMCR = 0.95$, $PAR_{\max} = 1$, $PAR_{\min} = 0.2$, $bw_{\max} = 3$, $bw_{\min} = 0.003$) [7], improved HS (IHS: $HMCR = 0.95$, $PAR_{\max} = 1$, $PAR_{\min} = 0.2$, $bw_{\max} = 3$, and $bw_{\min} = 0.003$) [20], and self-adaptive global HS (SGHS: $HMCR = 0.95$, $PAR_{max} = 1$, $PAR_{min} = 0.2$, $bw_{max} = 3$, and $bw_{min} = 0.003$) [21]. The population size in the investigated algorithms has been set to 100, except GGHS in which population size is 99. The maximum number of iterations in BMO algorithm is 500, whereas this value in HS-based algorithms is 2000. The parameters of the algorithms are set by trial and error.

The algorithms are executed in the MATLAB (The MathWorks, Inc., Natick, MA, USA) environment and run 10 times with random initial solutions. At the end of each run, the minimal objective function value is recorded. The mean (*Mean*), the best (*Best*), the worst (*Worst*), and the standard deviation (*Std*) of the objective function values obtained by GGHS, IHS, SGHS, and BMO algorithms have been summarized in Table II.

It is obvious from the results that the proposed BMO algorithm outperforms the other methods. Among the algorithms, the best performance belongs to BMO because it has found the minimal *Mean* and *Best* values. Moreover, the minimal *Std* value belongs to BMO, meaning that the robustness of this algorithm is more than that of the other algorithms. The performance of GGHS algorithm is better than the performance of IHS and SGHS in terms of all the indexes. The difference between the *Best* values obtained by GGHS and BMO is trivial, but in real problems, this difference is considerable. The importance of this trivial difference comes from the fact that any trivial reduction in the value of the objective function leads to a better

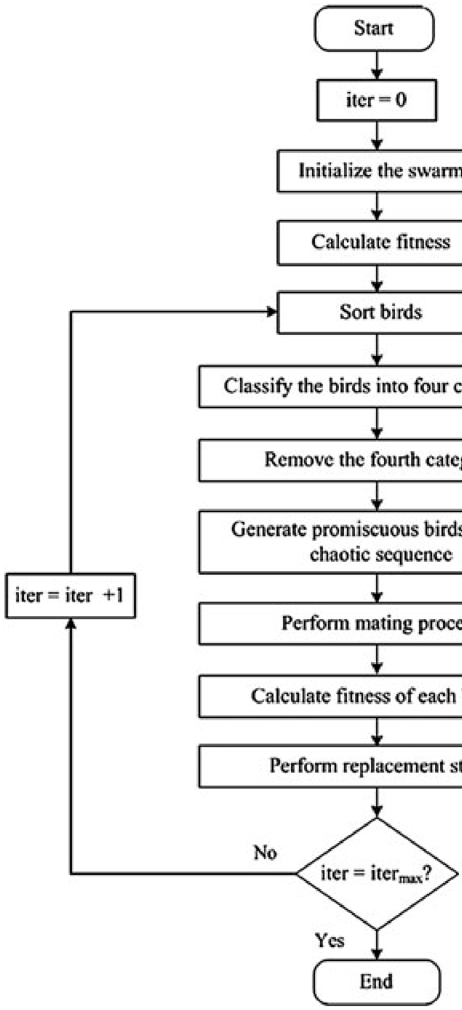

Figure 1. Flowchart of bird mating optimizer algorithm.

Table I. Upper and lower bounds of the model parameters.

Parameter	Upper bound	Lower bound
A (cm^2)	100	20
l (μm)	200	20
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

Table II. Comparison of BMO with the other algorithms in terms of the *Best*, the *Worst*, the *Mean*, and the *Std*.

Index	GGHS	IHS	SGHS	BMO
Best	2.84e−5	3.81e−5	3.38−5	2.73e−5
Worst	5.40e−5	8.82e−5	6.77e−5	2.85e−5
Mean	4.34e−5	5.66e−5	4.90e−5	2.77e−5
Std	7.42e−6	1.58e−5	1.12e−5	3.24e−7

GGHS, grouping-based global harmony search; IHS, improved harmony search; SGHS, self-adaptive global harmony search; BMO, bird mating optimizer.

knowledge about the real values of the unknown parameters. The optimal parameters related to the *Best* performance of the algorithms have been represented in Table III.

The success of BMO can be explained by considering some of its important aspects as follows.

1 *Distinct strategies to seek the search space*: BMO employs four distinct strategies to discover the optimum solution. Therefore, the algorithm has a

Table III. Comparison of the optimal parameters obtained by the algorithms.

Parameter	GGHS	IHS	SGHS	BMO
A	87.49	64.84	82.69	79.54
l	64.77	194.59	83.10	124.19
R_C	0.00078	0.00053	0.00055	0.00064
ξ_1	−1.1662	−0.9810	−0.9363	−1.0899
ξ_2	0.0040	0.0034	0.0036	0.0035
ξ_3	7.75e−5	7.56e−5	9.37e−5	6.20e−5
ξ_4	−1.39e−4	−1.32e−4	−1.66e−4	−1.29e−4
J_n	29.22	22.43	29.83	17.24
J_{max}	1008.02	1236.20	1115.41	1091.03
λ	14.74	20.80	22.76	19.12
b	0.0948	0.0332	0.1148	0.0844

GGHS, grouping-based global harmony search; IHS, improved harmony search; SGHS, self-adaptive global harmony search; BMO, bird mating optimizer.

more probability to efficiently explore the search space than the other methods.

2 *Using promiscuous birds for exploration*: Promiscuous birds, wandering with a chaotic behavior through as yet unseen regions of the search space, can provide good exploration during search process. This feature controls the diversity of the algorithm and avoids premature convergence.

3 *Using monogamous birds for exploration*: Monogamous birds stochastically select polyandrous birds (the birds with the best qualities) to follow them. This behavior provides relatively good exploitation through search space. Although monogamous birds may be gravitated toward selected females rapidly, resulting in clustering around local optima and occurring premature convergence, the other capabilities of the algorithm such as the other strategies, mutation factor, and time-varying weights can provide the facility of escaping from local minima.

4 *Using polygamous and polyandrous birds for exploration*: Polygamous and polyandrous birds make use of potential solutions, mix their information, and produce new candidate solutions. Combining the information of some good solutions and producing a new solution will increase the probability of finding global optimum more easily.

5 *More importance to better solutions*: In BMO, the most successful solutions have a more chance of being selected to produce new solutions. However, using the best solutions increases the probability of reaching to global optimum.

6 *Using weak solutions*: Using weak solutions by an optimization algorithm has some advantages. They may have some information with which the algorithm can reach the global solution more easily. Moreover, with the use of weak solutions, the algorithm is more efficient in maintaining the diversity. However, in each generation of BMO, the solutions with weak qualities have also a chance to produce new solutions.

In order to observe how the proposed algorithm converges to the optimal solution and jumps from each optimum to find the other best one, the objective function value is plotted versus the iteration index. Figure 2 illustrates this characteristic, indicating the minimal value of the objective function in each iteration related to the *Best* performance of BMO. As can be seen, the convergence speed of this algorithm is fast.

In order to verify the identification process, the optimal parameters obtained by BMO algorithm are put into the model, and polarization characteristic is plotted. As can be seen from Figure 3, the shapes of the fitted curves are very close to each other. Although the results are practically satisfactory, there are some errors between the experimental data and the simulated ones. It originates from the fact that FC is a complex nonlinear, multivariable, and strongly coupled system that is hard to model; therefore, many approximations and assumptions are considered during modeling. On the other hand, using more experimental data may increase the accuracy of the parameter identification problem. However, in this paper, the experimental data are limited because they stem from the literature [18].

Moreover, other important characteristics of the PEMFC are plotted, namely efficiency ($\eta = V/E_{nernst}$) and power ($P = Vi$). Figures 4 and 5 indicate that the η and P curves are close to the experimental values.

6. CONCLUSION

Because of the complexity of FC optimization problems, a novel heuristic optimization technique has been proposed to identify the unknown parameters of the Ballard Mark V FC. The proposed algorithm, trying to mimic the mating process of bird species during breeding season, has been named bird mating optimizer (BMO). BMO employs different ways to probe the search space, which have been inspired by real bird's strategies to mate. It has a simple

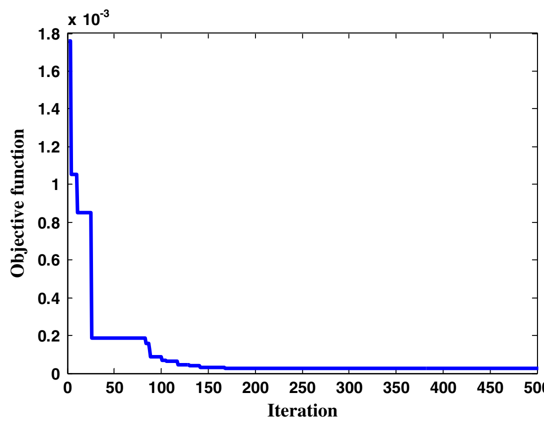

Figure 2. The objective function value during the identification process.

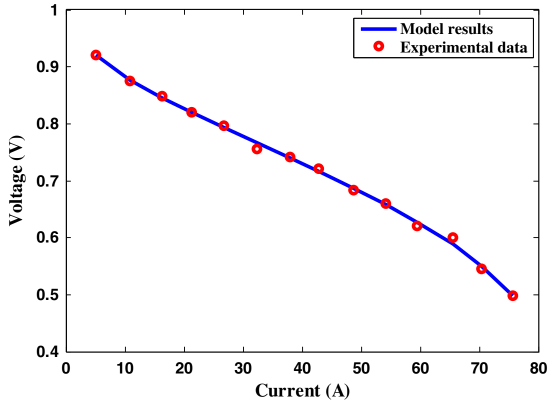

Figure 3. Comparison between the identified model and the experimental data.

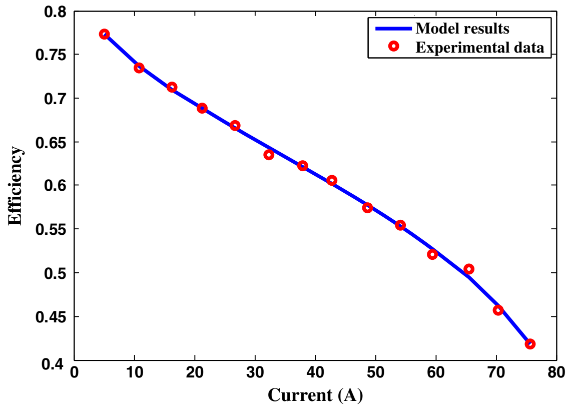

Figure 4. Efficiency curve of the identified model and the experimental data.

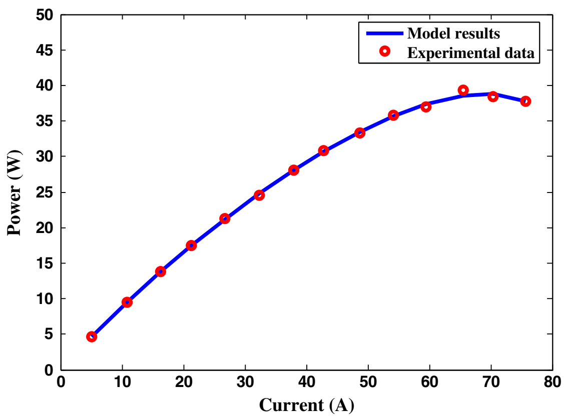

Figure 5. Power curve of the identified model and the experimental data.

concept, is easy to implement, uses different ways to escape from local optima, and tries to avoid premature convergence. The results show that the BMO not only has the best performance but also has high robustness. Therefore, BMO is a capable algorithm and can be efficiently applied to parameter identification of FC models.

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