Journal of Zhejiang University-SCIENCE C (Computers & Electronics)
ISSN 1869-1951 (Print); ISSN 1869-196X (Online)
www.zju.edu.cn/jzus; www.springerlink.com
E-mail: jzus@zju.edu.cn

A new artificial bee swarm algorithm for optimization of proton exchange membrane fuel cell model parameters*

Alireza ASKARZADEH, Alireza REZAZADEH
(*Faculty of Electrical and Computer Engineering, Shahid Beheshti University, G.C., Evin 1983963113, Tehran, Iran*)
E-mail: {a_askarzadeh, a-rezazade}@sbu.ac.ir

Received Oct. 11, 2010; Revision accepted Dec. 16, 2010; Crosschecked July 6, 2011

Abstract: An appropriate mathematical model can help researchers to simulate, evaluate, and control a proton exchange membrane fuel cell (PEMFC) stack system. Because a PEMFC is a nonlinear and strongly coupled system, many assumptions and approximations are considered during modeling. Therefore, some differences are found between model results and the real performance of PEMFCs. To increase the precision of the models so that they can describe better the actual performance, optimization of PEMFC model parameters is essential. In this paper, an artificial bee swarm optimization algorithm, called ABSO, is proposed for optimizing the parameters of a steady-state PEMFC stack model suitable for electrical engineering applications. For studying the usefulness of the proposed algorithm, ABSO-based results are compared with the results from a genetic algorithm (GA) and particle swarm optimization (PSO). The results show that the ABSO algorithm outperforms the other algorithms.

Key words: Proton exchange membrane fuel cell stack model, Parameter optimization, Artificial bee swarm optimization algorithm
doi:10.1631/jzus.C1000355 **Document code:** A **CLC number:** TP301.6; TM911

1 Introduction

Fuel cells have shown great potential to be the main candidate for providing electrical energy in the coming years. High efficiency, good dynamic response, high current density, trivial pollution, and low noise are among the important advantages of fuel cells that make them one of the most popular energy sources. A proton exchange membrane fuel cell (PEMFC) is the most popular type of fuel cell. It produces a quick response, has a low operational temperature which allows a fast start-up, produces no pollution if run with pure hydrogen, and uses a solid polymer electrolyte thereby reducing concerns about construction and safety (Mo *et al*., 2006).

Current research on PEMFC systems is focused on developing a proper and precise model that is able to portray a PEMFC's behavior with high degree of accuracy. An appropriate mathematical model can help researchers to simulate, evaluate, and control a PEMFC system. A variety of models have been developed for PEMFCs (Springer *et al*., 1991; Bernardi and Verbrugge, 1992; Fuller and Newman, 1993; Nguyen and White, 1993; Mann *et al*., 2000). Because a PEMFC is a nonlinear, multivariable, and strongly coupled system, many assumptions and approximations are considered during modeling. Thus, some differences are found between the model results and the real performance of PEMFCs. To increase the accuracy of models so that they match better the actual performance, optimization of PEMFC model parameters is essential.

Models that are easily solved and suitable for electrical engineering purposes are rarely available in the literature. In this investigation, a steady-state PEMFC model which is based on simulating the relationship between the output voltage and the

* Project supported by the Renewable Energy Organization of Iran (SANA)

partial pressures of hydrogen and oxygen is proposed. From an electrical engineering standpoint, an appropriate model is one that can portray the voltage versus current (*V-I*) curve (one of the most important characteristics of the PEMFC), facilitate the testing of PEMFC controllers, and evaluate the accessible power and energy for a certain load profile. Such a model can be a helpful tool for electrical engineering. A model contains many equations with various unknown parameters. Model equations portraying different phenomena depend on these parameters. The values of the model parameters are acquired mainly by laboratory experiments, and it is difficult to obtain them with great precision. To obtain better simulation results, the model parameters have to be optimized.

Due to the non-linearity and complexity of PEMFCs, traditional optimization methods cannot solve efficiently the parameter optimization problem. Therefore, a powerful optimization technique is needed to find the optimal parameters so that precise simulation results can be obtained. Because of their great potential, evolutionary-based optimization algorithms have attracted much attention in the field of parameter identification. In recent years, some researchers have applied genetic algorithms (GA) (Mo *et al*., 2006; Ohenoja and Leiviska, 2010), particle swarm optimization (PSO) (Ye *et al*., 2009), and simulated annealing (SA) (Outeiro *et al.*, 2008; 2009). GA, as the most popular type of evolutionary algorithm, gives better results than the traditional methods, but still has some deficiencies such as the lack of local search ability and premature convergence. PSO, inspired by the social behavior of bird flocking and fish schooling, is a swarm intelligence technique. Easy implementation, the small number of parameters to adjust, and fast convergence speed make PSO a high-performance algorithm. However, PSO's performance depends on its parameters and may be influenced by premature convergence and stagnation problems. Inspired by the process of annealing in metallurgy, an SA algorithm attempts to emulate this physical process and find the global optimum of optimization problems. The main drawback of SA algorithms is that there is not a rigorous theoretical foundation for determining their parameters, especially the parameters of the cooling schedule. The selection of these parameters is extremely difficult and the designer needs to trial in order to obtain values that will provide a proper optimization in a reasonable amount of computational time.

Motivated by the swarming behavior of honey bees, bee algorithms (BA) are recently invented methods which have been of significant interest to researchers in solving optimization problems. In a bee swarm, a powerful way to probe the search space is provided by using different bees. Different approaches have been developed for simulating the intelligent behavior of honey bees (Yang, 2005; Karaboga and Basturk, 2007; Akbari *et al*., 2010). In this investigation, an artificial bee swarm optimization algorithm, called ABSO, is proposed to optimize PEMFC stack model parameters. In the ABSO algorithm two kinds of bees are employed: onlookers and scouts. Each group utilizes a distinct moving pattern to probe the search space to find new food sources which have better nectars. The use of distinct moving patterns provides an opportunity to devise more capable algorithms compared to the other methods such as GA and PSO. To study the usefulness of the proposed algorithm, ABSO based results are compared with results from the GA and PSO methods. Finally, the ABSO algorithm is applied to optimize more parameters of the model.

2 Steady-state PEMFC stack model

In the standard operation of a PEMFC, hydrogen and an oxidant, usually from air, are supplied to the anode and cathode compartments, respectively. The total electrochemical cell reaction is given by

$$\mathrm{H_2} + \frac{1}{2}\mathrm{O_2} \longrightarrow \mathrm{H_2O}\text{+electricity+heat}. \tag{1}$$

The saturation pressure of water vapour $P_{\mathrm{H_2O}}^{\mathrm{sat}}$ (in atm, 1 atm=101.325 kPa), which is a function of the cell temperature T (K), is expressed by the following formula (Nguyen and White, 1993):

$$\begin{aligned}\lg P_{\mathrm{H_2O}}^{\mathrm{sat}} &= 2.95\times10^{-2}(T-273.15)\\ &\quad -9.18\times10^{-5}(T-273.15)^2\\ &\quad +1.44\times10^{-7}(T-273.15)^3-2.18.\end{aligned} \tag{2}$$

When air and H_2 are used as the reactants,

$$P_{N_2}^{channel} = \frac{0.79}{0.21} P_{O_2}, \tag{3}$$

$$P_{O_2} = P_c - H_{rc} \cdot P_{H_2O}^{sat} - P_{N_2}^{channel} \exp\left(\frac{0.291(i/A)}{T^{0.832}}\right). \tag{4}$$

When O_2 and H_2 are used,

$$P_{O_2} = H_{rc} \cdot P_{H_2O}^{sat} \cdot \left[\exp\left(-\frac{4.192(i/A)}{T^{1.334}}\right) \cdot \frac{P_c}{H_{rc} \cdot P_{H_2O}^{sat}} - 1\right]. \tag{5}$$

In each state, we have

$$P_{H_2} = 0.5 H_{ra} \cdot P_{H_2O}^{sat} \cdot \left[\exp\left(-\frac{1.635(i/A)}{T^{1.334}}\right) \cdot \frac{P_a}{H_{ra} \cdot P_{H_2O}^{sat}} - 1\right]. \tag{6}$$

In Eqs. (3)–(6), P_a is the anode inlet pressure (atm), P_c denotes the cathode inlet pressure (atm), H_{ra} represents the relative humidity of vapour in the anode compartment, H_{rc} shows the relative humidity of vapour in the cathode compartment, P_{H_2} and P_{O_2} are the partial pressures (atm) of hydrogen and oxygen respectively, $P_{N_2}^{channel}$ denotes the N_2 partial pressure (atm), A indicates the cell active area (cm^2), and i shows the cell current (A).

The output voltage of a stack can be obtained using the following formula (Nguyen and White, 1993; Mann *et al*., 2000):

$$V_S = n(E_{Nernst} - V_{act} - V_{ohmic} - V_{con}), \tag{7}$$

where V_S is the stack voltage (V), n is the number of series linked cells, E_{Nernst} denotes the fuel cell reversible voltage (V), and V_{act}, V_{ohmic}, and V_{con} are the activation, ohmic, and concentration voltage drops (V), respectively.

E_{Nernst} is the potential of the cell that is acquired in an open circuit thermodynamic balance (Mann *et al*., 2000):

$$E_{Nernst} = 1.229 - 0.85\times10^{-3}(T - 298.15) + 4.31\times10^{-5} T(\ln P_{H_2} + 0.5\ln P_{O_2}). \tag{8}$$

The concentration of dissolved oxygen C_{O_2} (mol/cm^3) at the interface of the cathode catalyst can be obtained by Henry's law as follows:

$$C_{O_2} = \frac{P_{O_2}}{5.08\times10^6 \times e^{-498/T}}. \tag{9}$$

The activation voltage drop V_{act}, which is caused by the sluggish kinetics of the reactions, can be computed as follows (Mann *et al*., 2000):

$$V_{act} = -(\xi_1 + \xi_2 T + \xi_3 T \ln C_{O_2} + \xi_4 T \ln i), \tag{10}$$

where ξ_1, ξ_2, ξ_3, and ξ_4 represent parametric coefficients based on electrochemistry, thermodynamics, and fluid mechanics (Mann *et al*., 2000).

The ohmic voltage drop V_{ohmic}, which is caused by the voltage drop through the equivalent membrane resistance R_M and contact resistances R_C, both between the membrane and electrodes, and between the electrodes and the bipolar plates, can be formulated using Ohm's law as follows:

$$V_{ohmic} = i(R_M + R_C). \tag{11}$$

The equivalent resistance of the membrane can be obtained by

$$R_M = \rho_M \cdot l / A, \tag{12}$$

where ρ_M is the specific resistivity (Ω·cm) of the membrane for the electron flow and l denotes the thickness (cm) of the membrane.

Nafion is a registered trademark of Dupont and Nafion membranes are the most widely used in PEMFC systems. Dupont uses Nafion 117 (l=178 μm), Nafion 115 (l=127 μm), and Nafion 112 (l=51 μm) as product designations to represent the thickness of its products.

The following numeric expression is used to determine the resistivity of Nafion membranes (Mann *et al*., 2000):

$$\rho_M = \frac{181.6[1 + 0.03(i/A) + 0.062(T/303)^2 (i/A)^{2.5}]}{[\lambda - 0.634 - 3(i/A)]\exp[4.18(T-303)/T]}, \tag{13}$$

where λ is the water content of the membrane. This is a tunable parameter with a possible maximum value of 23. Under the ideal condition of 100% relative humidity, it may have a value of 14.

The concentration voltage drop V_{con}, caused by the mass transportation, affects the concentrations of hydrogen and oxygen and can be computed by

$$V_{con} = -b \ln(1 - J / J_{max}), \tag{14}$$

where b is a parametric coefficient (V), J is the current density (A/cm^2), and J_{max} denotes the maximum current density (A/cm^2), with which the cell operates at a rate similar to the maximum supply speed.

3 Parameter optimization of the PEMFC stack model

With the results obtained experimentally from the system, the parameters of the PEMFC stack model can be extracted with the help of an optimization method. To fit the mathematical model to the experimental data, it is essential to optimize the values of the model parameters. In Mo *et al*. (2006) seven parameters including ξ_1, ξ_2, ξ_3, ξ_4, λ, R_C, and b have been optimized based on a GA. In this study, first, the values of these parameters are optimized using the ABSO algorithm and then the results are compared with those from the PSO algorithm and the published results. Then, more parameters including ξ_1, ξ_2, ξ_3, ξ_4, λ, R_C, b, and J_{max} are considered and optimized using the ABSO algorithm.

The objective function is defined by comparing the results obtained using these parameters in the mathematical model with the results obtained experimentally from the PEMFC system, and is given by

$$\min\left(F = \sum_{q=1}^{Q} (V_{sm}^q - V_S^q)^2\right), \tag{15}$$

where F is the objective function, V_{sm}^q is the voltage of the qth data point obtained experimentally, V_S^q is the output voltage of the qth data point of the mathematical model, and Q denotes the number of the experimental data points.

The experimental data were adopted from the curves indicated by Mo *et al*. (2006). The parameters and operational range of the studied stack are shown in Table 1. From the adopted data, two sets (3/5×10^5 Pa, 353.15 K; 1/1×10^5 Pa, 343.15 K) were used to optimize the PEMFC model parameters and two sets (2.5/3×10^5 Pa, 343.15 K; 1.5/1.5×10^5 Pa, 343.15 K) were used for the validation of the optimized model.

Table 1 Parameters and operational ranges of the stack

Stack parameter	Value	Stack parameter	Value
n	24	P_a (×10^5 Pa)	1.0–3.0
A (cm^2)	27	P_c (×10^5 Pa)	1.0–5.0
l (μm)	127	T (K)	343.15–353.15
J_{max} (mA/cm^2)	860	H_{ra}	1
Rated power (W)	250	H_{rc}	1

4 The proposed artificial bee swarm optimization algorithm

The collection and processing of nectar are instances of intelligent behaviors of honey bees. The main difference between a bee swarm and other population-based algorithms is that in a bee swarm different kinds of bees are employed which use different types of trajectories to amend their positions.

In this research, each food source is regarded as a position (feasible solution) in the food source region and the objective function of each bee indicates the quality of the food source discovered by it. In the ABSO algorithm, the bees leave their hive to find new food sources and return to it to share their observations in relation to the quality of the discovered food sources. The bees are then partitioned into two groups according to the quality of the best food source they have discovered so far. The ABSO algorithm employs two types of bees: onlookers and scouts. The percentage of each group is selected arbitrarily. In general, it is better that a minor fraction of the bees is utilized as scouts, and the rest used as onlookers. For assigning each bee to a related group, the bees are ranked in light of their objective functions. In this case, the lesser is the value of the objective function, the better is the bee. Then, a predefined portion of the bees that have the worst objective functions are chosen as scout bees and the others are selected as onlookers. Each group makes use of a dissimilar moving strategy to explore the food source area. A random flying strategy is employed by the scout bees to fly over the food source area.

Among the onlooker bees, n_e bees with the better objective functions are chosen as elite bees. Each hive includes a dance region in which each elite bee dances and tries to encourage the onlooker bees to seek out the best food source it has discovered so far. The way in which each onlooker bee makes a decision to follow a specific dancer is not obvious, but is likely to be related to the quality of the nectar source. Accordingly, as the quality of a food source increases, that food source has a greater chance of being selected. The value of n_e plays an important role. If the n_e selected is very low, this may result in premature convergence. If the chosen n_e is too large, this may have a bad effect on the search ability of the ABSO algorithm.

A scout bee is employed to explore randomly the food source region to discover new food sources. It adjusts its position with a random function. The ABSO algorithm utilizes the scout bees to manage the diversity of the swarm. Generally speaking, increasing diversity is an efficient method to mitigate the stagnation problem. Each scout bee adjusts its position as follows:

$$x_j^k(\text{iter}+1) = x_j^k(\text{iter}) + r_\text{s} \cdot \text{Rf}_j(\text{iter}), \quad k = 1, 2, .., n_\text{s}, \ j = 1, 2, ..., d, \tag{16}$$

where k denotes the bee's index, n_s is the number of scout bees, j is the parameter's index, d denotes the problem dimension, r_s is a random number between –1 and 1, iter denotes the iteration index, and **Rf** is a vector depending on the bounds of the variables in which its radius τ decreases with a linear function from a large value ($\tau_{\max}$) to a small value ($\tau_{\min}$) during iterations as follows:

$$\tau = \tau_{\max} - (\tau_{\max} - \tau_{\min})\text{iter}/\text{iter}_{\max}, \tag{17}$$

where $\text{iter}_{\max}$ is the maximum number of iterations. The large value of τ in the first iterations facilitates the scout bees to search globally and a small value in the last iterations allows them to probe locally. **Rf** is defined as follows:

$$\mathbf{Rf}(\text{iter}) = \tau(\text{iter}) \cdot (|u_1 - l_1|, |u_2 - l_2|, ..., |u_d - l_d|), \tag{18}$$

where l_j and u_j are the lower and upper bounds of the jth variable, respectively.

Each onlooker bee has a memory to remember the decisions that it has made so far and their achievement. In each iteration of the ABSO algorithm, each onlooker bee uses a probabilistic method to select one of the dancers as its own interesting elite bee. Then, it adjusts its position using its own knowledge and that of its interesting elite bee. Consequently, the position of the kth onlooker bee is adjusted via two best values. The first is the best position achieved by itself so far, denoted as x^{bk}, and the second is the best position obtained so far by its interesting elite bee, denoted as x^{ek}. Each onlooker bee adjusts its position according to Eq. (19):

$$\begin{aligned} x_j^k(\text{iter}+1) &= x_j^k(\text{iter}) + w_\text{b} \cdot r_\text{b}(x_j^{\text{b}k}(\text{iter}) \\ &\quad - x_j^k(\text{iter})) + w_\text{e} \cdot r_\text{e}(x_j^{\text{e}k}(\text{iter}) - x_j^k(\text{iter})), \\ k &= 1, 2, ..., n_\text{o}, \ j = 1, 2, ..., d, \end{aligned} \tag{19}$$

where n_o is the number of the onlooker bees and r_b and r_e are random numbers from the interval [0, 1]. To make a trade-off between global and local searches, w_b and w_e are defined as decreasing linear functions. For enhancing the global search in the beginning of the algorithm, each onlooker bee employs its maximum values ($w_{b\max}$ and $w_{e\max}$) and for converging towards an optimal solution it terminates its search using its minimum values ($w_{b\min}$ and $w_{e\min}$). The parameters of w_b and w_e are defined as follows:

$$w_\text{b} = w_{\text{b}\max} - (w_{\text{b}\max} - w_{\text{b}\min})\text{iter}/\text{iter}_{\max}, \tag{20}$$

$$w_\text{e} = w_{\text{e}\max} - (w_{\text{e}\max} - w_{\text{e}\min})\text{iter}/\text{iter}_{\max}. \tag{21}$$

In this work, the tournament selection approach is used by each onlooker bee to select its interesting elite bee. Tournament selection is a method of selecting an individual from a group, which is usually used in GA.

The steps of the tournament selection approach are as follows:

Step 1: the tournament size t_s (number of participants) is set.

Step 2: based on Eq. (22), the tournament participants tp are selected from dancers:

$$\text{tp} = \text{ceil}(n_\text{e} \cdot \text{rand}(1, \ t_\text{s})), \tag{22}$$

where rand(1, t_s) generates a random vector drawn from a uniform distribution on the unit interval in which its length is equivalent to t_s and ceil(·) rounds it towards infinity.

Step 3: the winner of the tournament (the one with the best objective function) is chosen as the interesting elite bee for the onlooker bee.

In tournament selection, weak dancers have a smaller chance of being chosen when the tournament size is large. This approach has various merits: it is simple to execute, operates on parallel architecture, and permits the selection pressure to be adjusted easily by the tournament size.

The steps of the proposed algorithm used in this study to obtain the optimal parameters are presented as follows:

Step 1: initially, the number of bees (n_b), percentage of onlooker bees (p_o), percentage of scout bees (p_s), maximum number of iterations (iter_{max}), and other adjustable parameters are determined. At the beginning of the algorithm all the bees are randomly initialized as follows:

$$x_j^i = l_j + \alpha \cdot (u_j - l_j),\quad i = 1, 2, ..., n_b,\quad j = 1, 2, ..., d, \tag{23}$$

where α is a random number between 0 and 1.

Step 2: based on Eq. (15), the objective function of each bee is computed.

Step 3: the bees are ranked according to their objective functions. In this case, the lesser is the objective function value, the better is the bee.

Step 4: the swarm is partitioned into two groups: onlookers and scouts.

Step 5: the new position of each scout bee is adjusted using Eq. (16).

Step 6: elite bees are specified.

Step 7: each onlooker bee selects its own interesting elite bee among the dancers using a tournament selection approach, and then adjusts its new position using Eq. (19).

Step 8: with new positions, all the bees are checked to see whether they are in the search space. If any bee is found to be outside of the search space, it is returned to its previous position.

Step 9: steps 2 to 8 are repeated until the predefined number of iterations iter_{max} is reached.

5 Experiments

5.1 Settings of the ABSO algorithm

In this investigation, the adjustable variables used in the ABSO algorithm are given by n_b=20, p_o=0.8, p_s=0.2, n_e=10, $w_{b\max}$=$w_{e\max}$=2.5, $w_{b\min}$=$w_{e\min}$=1.25, t_s=2, iter_{max}=5000, τ_{max}=0.2, and τ_{min}=0.02. Note that these parameters were adjusted by trial and error and no attempt was made to optimize them.

5.2 Simulation results

Seven parameters including ξ_1, ξ_2, ξ_3, ξ_4, λ, R_C, and b were optimized via the ABSO algorithm which was executed in the Matlab environment. The bounds of the model parameters are shown in Table 2 (Mo *et al*., 2006).

Table 2 Bounds of the model parameters

Model parameter	Upper bound	Lower bound
ξ_1	−0.944	−0.952
ξ_2	0.005	0.001
ξ_3	7.8×10^{-5}	7.4×10^{-5}
ξ_4	-1.88×10^{-4}	-1.98×10^{-4}
λ	23	14
R_C (Ω)	0.0008	0.0001
b (V)	0.500	0.016

To assess the efficiency of the ABSO algorithm, the results were compared with the results of the PSO algorithm and results reported in the literature from the use of a hybrid genetic algorithm (HGA) and a simple genetic algorithm (SGA) (Mo *et al*., 2006). The comparison of results is shown in Table 3. The results obtained using the ABSO algorithm were more accurate than those from using the GA and PSO algorithms, because the objective function value obtained by the ABSO algorithm was lower than those of the other methods. To verify the performance of the PEMFC stack model which was optimized using the ABSO algorithm, a voltage versus current curve of the PEMFC stack with the optimal parameters was plotted (Fig. 1a). The validated results of the optimized model are shown in Fig. 1b. The accuracy of the results, indicated in Fig. 1, clearly reveals the usefulness of the fuel cell model and the proposed optimization method. The output voltage of the mathematical model agrees

Table 3 Values of the optimized parameters

Parameter	Value			
	ABSO	PSO	HGA	SGA
ξ_1	−0.951999	−0.951417	−0.944957	−0.947310
ξ_2	3.09090×10^{-3}	3.10490×10^{-3}	3.01801×10^{-3}	3.06410×10^{-3}
ξ_3	7.800×10^{-5}	7.691×10^{-5}	7.401×10^{-5}	7.713×10^{-5}
ξ_4	-1.880×10^{-4}	-1.915×10^{-4}	-1.880×10^{-4}	-1.939×10^{-4}
λ	23	22.3758	23	19.7650
R_C (Ω)	1.0000×10^{-4}	5.7092×10^{-4}	1.0000×10^{-4}	2.7197×10^{-4}
b (V)	0.0328680	0.0339780	0.0291448	0.0239810
F	9.180218	11.255417	16.608194	20.810000

ABSO: artificial bee swarm optimization; PSO: particle swarm optimization; HGA: hybrid genetic algorithm; SGA: simple genetic algorithm

well with the experimental data. There are some errors in the results, but they are acceptable in engineering. Through evolution of the objective function, the convergence of the proposed method can be analyzed. Fig. 2 indicates the convergence process of the ABSO algorithm and shows the best objective function value versus the number of iterations.

Due to the efficiency of the ABSO algorithm, it is easy to consider more uncertain parameters. A parameter such as J_{max} can be considered as a parameter that needs to be optimized. The lower and upper bounds of this parameter were set at 500 and 1500 mA/cm^2, respectively (Corrêa *et al*., 2004).

The parameters of the optimized PEMFC stack model are listed in Table 4. The objective function values reported in Table 4 show that when more parameters of the stack model are appended to the optimization problem, the accuracy of the results improves.

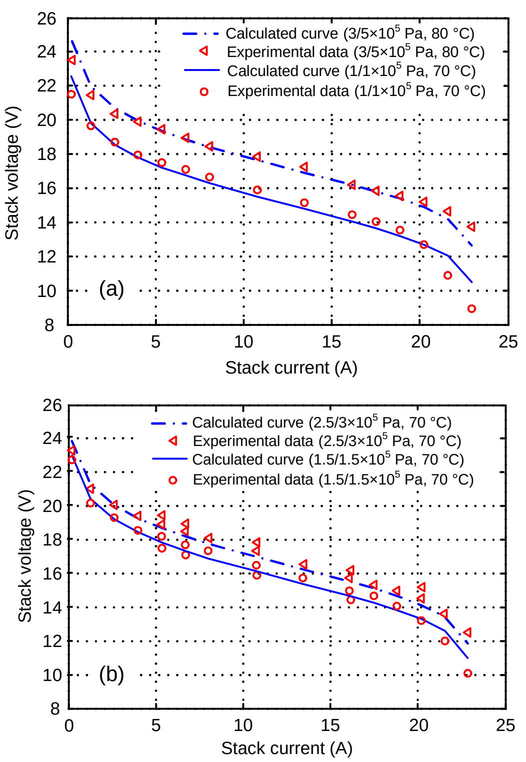

Fig. 1 The PEMFC voltage versus current curves obtained by the ABSO algorithm and the experimental data considering seven parameters
(a) Optimized model; (b) Validation

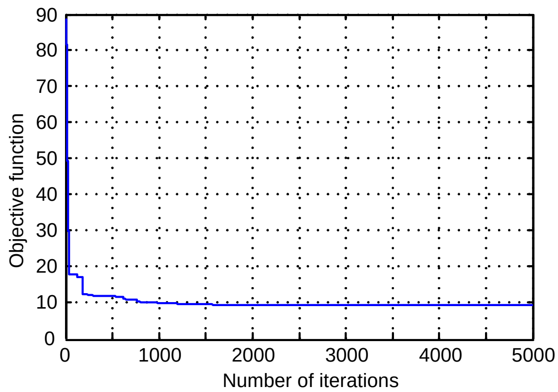

Fig. 2 Convergence process of the ABSO algorithm during iterations considering seven parameters

Table 4 Values of the optimized parameters of the PEMFC stack model

Parameter	Value	Parameter	Value
ξ_1	−0.951999	R_C (Ω)	1.0000×10^{-4}
ξ_2	3.08500×10^{-3}	b (V)	0.0278930
ξ_3	7.800×10^{-5}	J_{max} (mA/cm^2)	844.780
ξ_4	-1.880×10^{-4}		
λ	23	F	8.337850

After the identification process, the obtained parameters identified by the ABSO algorithm are returned to the mathematical model to obtain the PEMFC characteristics. With the optimal parameters, voltage versus current characteristics of the optimized stack are shown in Fig. 3a. The validation results of the optimized model and the convergence process of the proposed algorithm are shown in Figs. 3b and 4, respectively.

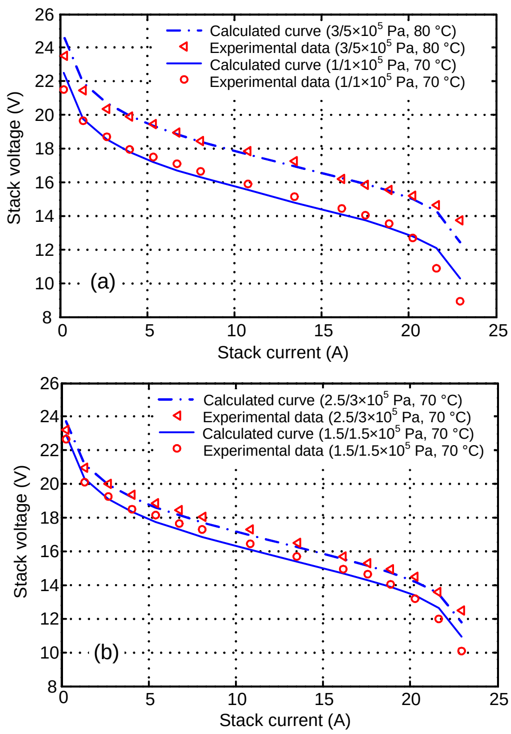

Fig. 3 The PEMFC voltage versus current curves obtained by the ABSO algorithm and the experimental data considering eight parameters
(a) Optimized model; (b) Validation

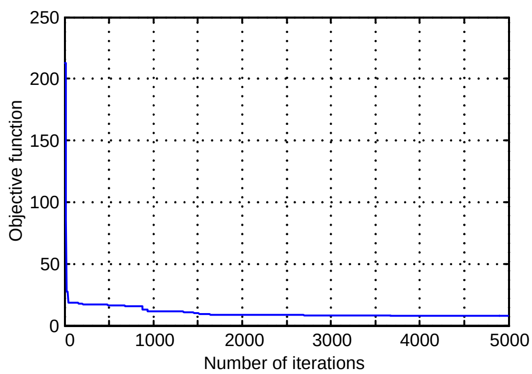

Fig. 4 Convergence process of the ABSO algorithm during iterations

To further verify the validity of the parameter optimization process, two important characteristics of the PEMFC, including the efficiency which is defined by $\eta=V_S/E_{Nernst}$ (Jia *et al.*, 2009) and the output power, are plotted in Figs. 5 and 6.

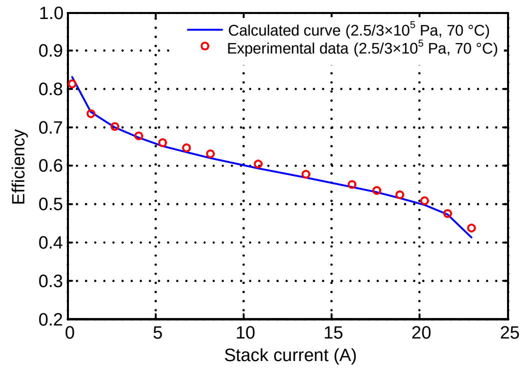

Fig. 5 The PEMFC efficiency curve obtained by the ABSO algorithm and experimental data

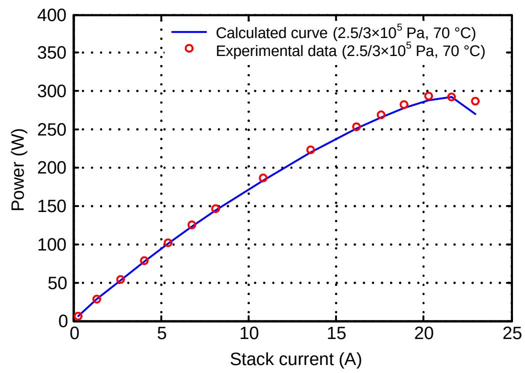

Fig. 6 The PEMFC output power curve obtained by the ABSO algorithm and experimental data

We conclude that the ABSO algorithm is a capable optimization technique which can efficiently solve the parameter optimization problem of PEMFCs.

6 Conclusions

In this paper, an artificial bee swarm optimization algorithm, called ABSO, is proposed for optimizing the parameters of a PEMFC stack model. We show that the performance of the proposed algorithm is satisfactory and that the results acquired by the ABSO algorithm outperform those from GA and PSO algorithms. Therefore, the ABSO algorithm is an effective and reliable technique which can be applied to solve parameter optimization problems of fuel cell models.

References

Akbari, R., Mohammadi, A., Ziarati, K., 2010. A novel bee swarm optimization algorithm for numerical function optimization. *Commun. Nonl. Sci. Numer. Simul.*, **15**(10): 3142-3155. [doi:10.1016/j.cnsns.2009.11.003]

Bernardi, D.M., Verbrugge, M.W., 1992. A mathematical model of the solid-polymer-electrolyte fuel-cell. *J. Electrochem. Soc.*, **139**(9):2477-2491. [doi:10.1149/1.2221251]

Corrêa, J.M., Farret, F.A., Canha, L.N., Simões, M.G., 2004. An electrochemical-based fuel-cell model suitable for electrical engineering automation approach. *IEEE Trans. Ind. Electr.*, **51**(5):1103-1112. [doi:10.1109/TIE.2004.834972]

Fuller, T.F., Newman, J., 1993. Water and thermal management in solid-polymer-electrolyte fuel-cells. *J. Electrochem. Soc.*, **140**(5):1218-1225. [doi:10.1149/1.2220960]

Jia, J., Li, Q., Wang, Y., Cham, Y.T., Han, M., 2009. Modeling and dynamic characteristic simulation of a proton exchange membrane fuel cell. *IEEE Trans. Energy Conv.*, **24**(1):283-291. [doi:10.1109/TEC.2008.2011837]

Karaboga, D., Basturk, B., 2007. A powerful and efficient algorithm for numerical function optimization: artificial bee colony (ABC) algorithm. *J. Glob. Optim.*, **39**(3): 459-471. [doi:10.1007/s10898-007-9149-x]

Mann, R.F., Amphlett, J.C., Hooper, M.A.I., Jensen, H.M., Peppley, B.A., Roberge, P.R., 2000. Development and application of a generalised steady-state electrochemical model for a PEM fuel cell. *J. Power Sources*, **86**(1-2): 173-180. [doi:10.1016/S0378-7753(99)00484-X]

Mo, Z.J., Zhu, X.J., Wei, L.Y., Cao, G.Y., 2006. Parameter optimization for a PEMFC model with a hybrid genetic algorithm. *Int. J. Energy Res.*, **30**(8):585-597. [doi:10.1002/er.1170]

Nguyen, T.V., White, R.E., 1993. A water and heat management model for proton-exchange-membrane fuel-cells. *J. Electrochem. Soc.*, **140**(8):2178-2186. [doi:10.1149/1.2220792]

Ohenoja, M., Leiviska, K., 2010. Validation of genetic algorithm results in a fuel cell model. *Int. J. Hydr. Energy*, **35**(22):12618-12625. [doi:10.1016/j.ijhydene.2010.07.129]

Outeiro, M.T., Chibante, R., Carvalho, A.S., de Almeida, A.T., 2008. A parameter optimized model of a proton exchange membrane fuel cell including temperature effects. *J. Power Sources*, **185**(2):952-960. [doi:10.1016/j.jpowsour.2008.08.019]

Outeiro, M.T., Chibante, R., Carvalho, A.S., de Almeida, A.T., 2009. A new parameter extraction method for accurate modeling of PEM fuel cell. *Int. J. Energy Res.*, **33**(11):978-988. [doi:10.1002/er.1525]

Springer, T.E., Zawodzinski, T.A., Gottesfeld, S., 1991. Polymer electrolyte fuel-cell model. *J. Electrochem. Soc.*, **138**(8):2334-2342. [doi:10.1149/1.2085971]

Yang, X.S., 2005. Engineering optimizations via nature-inspired virtual bee algorithms. *LNCS*, **3562**:317-323. [doi:10.1007/11499305_33]

Ye, M., Wang, X., Xu, Y., 2009. Parameter identification for proton exchange membrane fuel cell model using particle swarm optimization. *Int. J. Hydr. Energy*, **34**(2):981-989. [doi:10.1016/j.ijhydene.2008.11.026]