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Review Article

Parameter Estimation of Polymer Electrolyte Membrane Fuel Cell Using Sine-Cosine Algorithm

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Abstract: Polarization curves of polymer electrolyte membrane fuel cell are based on several parameters. Parameter importance differs relatively to the model specification. The aim of this paper is to obtain an accurate model by validating the model at different conditions. Its model is complicated, non-linear, and multi variable model because it needs to estimate some model parameters according to their possible ranges. In this paper, sine-cosine algorithm is a meta heuristic technique inspired from mathematical equations to estimate seven unknown parameters to develop the model accuracy. Several tests are applied to prove the superiority of the algorithm compared to two other algorithms and validate the model performance.

Keywords: fuel cell, proton exchange membrane fuel cell, polymer electrolyte membrane fuel cell, polarization curve, sine-cosine algorithm, Meta-heuristic.

INTRODUCTION

The environmental bad effects, exhaustion of fossil fuel, and increasing demand of energy resources are main reasons that have encouraged towards the renewable energy in the last few decades. Fuel cells is one of the most promising sources to produce electrical power(Wang, Chen, Mishler, Cho, & Adroher, 2011). Fuel cells can be used in wide range as a backup power source in many stationary and portable applications due to their specifications like weather, spacecraft stations, and vehicles. They produce electrical energy through electro-chemical reaction in which chemical energy is converted into electrical energy(Yang & Wang, 2012). High efficiency, low environmental pollution, and reliability are some merits of the fuel cells(Correa, Farret, Popov, & Simoes, 2005; Wang et al., 2011). Fuel cell basically consists of anode and cathode electrodes with electrolyte between them. Fuel cell type differs according to the electrolyte material and the start-up time required. Proton Exchange Membrane Fuel Cell or polymer electrolyte membrane fuel cell (PEMFC) has a start-up time equals one second. However, Solid Oxide Fuel cell has a start-up time equals ten minutes(Yang & Wang, 2012). Any practical model requires higher voltage range. But the fuel cell output voltage range is from 0.5 to 0.9v. So, the fuel cell stack model consists of group of cells connected in series(Corrêa, Farret, Canha, & Simoes, 2004). PEMFC fuel cell has some merits like high efficiency, low operating temperature (range 70°C: 85°C) and pressure. So, PEMFC is widely used in many applications as a prominent power source(Niu, Zhang, & Li, 2014).

In order to improve PEMFC system performance, PEMFC mathematical model is used. PEMFC Modelling makes the designing and testing of the cell easier(Yang & Wang, 2012). PEMFC model requires extracting the effective value of some parameters. The prediction process of PEMFC parameters is so difficult due to non-linear, multi variable system. So, metaheuristic algorithms are used to extract the value of some model parameters(Askarzadeh & Rezazadeh, 2011; Mo, Zhu, Wei, & Cao, 2006). Study of the literature produces many metaheuristic algorithms such as Particle Swarm Optimization algorithm(Mendes, Kennedy, & Neves, 2004), Genetic Algorithm(Mitchell, 1998), Artificial Bee Colony algorithm(ABC)(Karaboga & Basturk,

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2007), Grey Wolf Optimizer algorithm, Harmony Search that has been optimized for PEMFC Parameter estimation. Sine-Cosine Algorithm (SCA) is a population-based optimization algorithm that inspired from the sine-cosine mathematical model(Mirjalili, 2016).

In this study, SCA is used to extract PEMFC parameters to close the model to PEMFC stack. SCA is compared to two other algorithms to illustrate the superior algorithm, performance, and efficiency for PEMFC based on some comparisons.

This paper is organised in the next three sections. Section 2 contains PEMFC model and its objective function. Section 3 contains SCA and its sequential steps. Section 4 contains results of SCA applied to PEMFC and results discussion. Section 5 contains the conclusion.

2. PEMFC model

The electrochemical model is widely used to evaluate PEMFC model performance(Amphlett et al., 1995). However, E_{Nernst} is an equilibrium voltage. PEMFC model has three types of voltage drop such as activation voltage V_{act}, concentration voltage V_{con}, and ohmic loss V_{ohmic}. So, the fuel cell output voltage is represented as follows in equation 1. V_{act} is responsible for voltage drop at high current(Mo et al., 2006).

$$V_{fc} = n = (E_{nernst} - V_{act} - V_{ohm} - V_{con}) \qquad (1)$$

$$V = 1.229 - 0.85 \text{ x } 10^{-3}(\text{T} - 298.15) + 4.3085 \text{ x } 10^{-5} \text{ x T} (\ln P_{H_2} + 0.5 \ln P_{O_2}) + [\xi_1 + \xi_2 . T + \xi_3 . T . \ln C_{O_2} + \xi_4 . T . \ln i] - i.(R_m + R_c) + b. \ln\left(1 - \frac{I}{I_{max}}\right) \qquad (2)$$

Where n is the used fuel cell number. E_{Nernst} in volt depends on the operating conditions like T is a cell temperature in Kelvin, P_{H_2} and P_{O_2} are hydrogen and oxygen partial pressures in atm. V_{act} in volt is voltage drop caused by slowness of the electrochemical reaction. V_{act} in volt depends on four coefficients ξ_1, ξ_2, ξ_3, ξ_4, oxygen concentration at cathode C_{O_2} in mol/cm3, cell current i in ampere and T. V_{ohmic} in volt is the sum of flow resistance of electrons and ions that depends on cell current. V_{con} in volt is caused due to changes in concentration of reactants that depends on coefficient B in volt, current density I , and maximum current density I_{max} in mA/cm2. So, set of PEMFC model parameters ξ_1, ξ_2, ξ_3, ξ_4, B, R_c, λ need to be picked precisely(Saeed & Warkozek, 2015; Ye, Wang, & Xu, 2009). The final target is to fit the experimental real data over the simulated date obtained by equation 2 as objective function SSE in equation 3.

$$SSE = \sum_{q=1}^{N} (V_e - V_s)^2 \qquad (3)$$

Where Ve is the experimental voltage, Vs is the simulated voltage, and N is the number of data points used for the estimation process(Mo et al., 2006).

3. Sine-Cosine Algorithm (SCA)

SCA is a metaheuristic algorithm inspired from sine cosine mathematical functions. It is like any other algorithms used to optimize the parameters of the problems(Mirjalili, 2016). SCA is a population-based algorithm that starts with random set of search agents called population in the search space. SCA used sine-cosine functions to update population positions towards the optimal solution as in equation 4.

$$x_i^{t+1} = \begin{cases} x_i^t + r_1 * \sin(r_2) * |r_3 * p_i^t - x_i^t| & r_4 \geq 0.5 \\ x_i^t + r_1 * \cos(r_2) * |r_3 * p_i^t - x_i^t| & r_4 < 0.5 \end{cases} \qquad (4)$$

Where x_i is the solution position, t is a current iteration, x_i^{t+1} is the updated position at the next iteration, p_i is the global solution, r_1, r_2, r_3, and r_4 are SCA parameters that used to balance exploration and exploitation of the algorithm. r_1 varies linearly from an integer constant called a as in equation 5 to indicate next position region. r_2 is random number varying in interval [0, 2π]. r_3 is random weight of current position for the next position. r_4 switches equally between sine and cosine equations. T is a maximum number of iterations.

$$r_1 = a - t * \frac{a}{T} \qquad (5)$$

The steps of SCA as in fig1 that represent the sequential steps of the algorithm

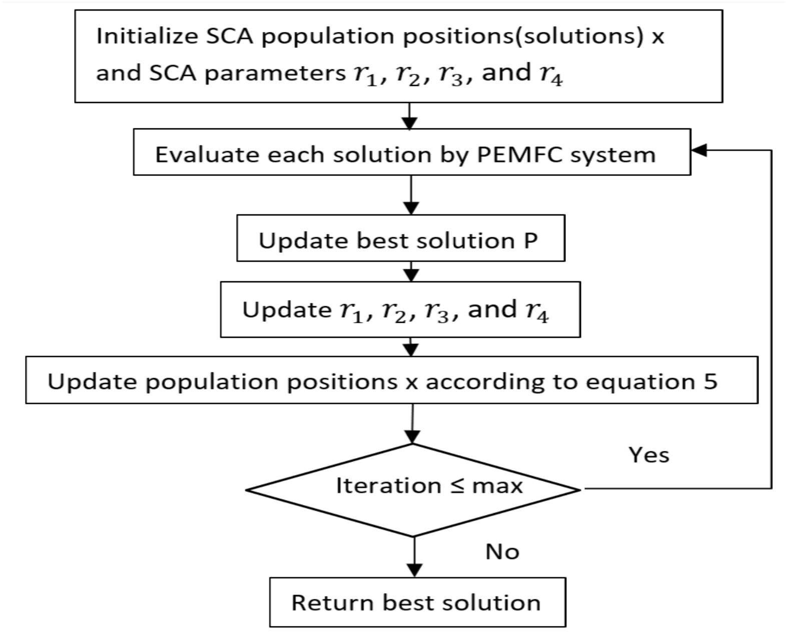

Fig1. SCA procedures flow chart

4. RESULTS AND DISCUSSION

This study aims to extract PEMFC set of parameters that close to the actual fuel cell characteristics to reach the optimal solution. Four PEMFC model's data sets are used to identify and valid PEMFC system. The characteristics of the used models for the polarization curves are 3/5 bar, 353.15°K, 1/1 bar, 343.15°K, 2.5/3 bar, 343.15°K and 1.5/1.5 bar, 343.15°K. The first two models are used for extracting the unknown parameters. Where the others are used to test and valid the system. PEMFC system operates at conditions as in table 1. The unknown parameters ranges are as in table 2.

Table1. known PEMFC stack parameters (Mo et al., 2006).

Stack parameter	value	Stack parameter	value
n	24	P_a (bar)	1.0 – 3.0
$A(cm^2)$	27	P_c (bar)	1.0 – 5.0
ℓ(μm)	127	T (K)	343.15 – 353.15
I_{max} $(mA.cm^{-2})$	860	RH_a	1.0
Power(w)	250	RH_c	1.0

Table 2. PEMFC model parameter boundaries(Askarzadeh, 2013; Zhang & Wang, 2013).

Model parameter	ξ_1	ξ_2	ξ_3	ξ_4	λ	R_c		b
Upper bound	-1.19969	0.005	$9.8x\ 10^{-5}$	$-9.54x\ 10^{-4}$	24	0.0008	0.5	
Lower bound	-0.8532	0.001	$3.6x\ 10^{-5}$	$-2.6x\ 10^{-4}$	10	0.0001	0.0136	

SCA has the ability to explore the parameter spaces after few numbers of iterations. So, SCA helps to reduce the system error and find good solution. SCA is compared to ABC and Salp Swarm Algorithm (SSA)(Mirjalili et al., 2017). They are developed in MATLAB and performed using intel core i7 1.8 GHz processor and 12GRAM. SCA processes at a=2, r3=0.7, r2 and r4 are random values during the ranges. ABC acceleration coefficient (a) equals 1 and 0.6 trial limit and the other parameters are random values during ranges. Identification case statistical comparison contains obtained minimum error (Best), obtained maximum error (Worst), mean error (Mean), and standard deviation (Std. dev) as in table 3. These algorithms' results are obtained after 200 iteration, 30 solution, 7 unknown parameters, and repeating the process 500 times. After processing, extracted parameters, identification sum square error (I. SSE), validation sum square error (V. SSE), and processing time (P. time) are in table 4.

***Table3.* Statistical comparison of SCA results of PEMFC identification case with SSA and ABC**

	ABC	SSA	SCA
Best	0.36308748	0.25967074	0.50806551
Mean	4.85440607	275.362582	7.32386302
Std. dev	3.21384142	275.966054	6.95875769
Worst	17.2891888	1916.20751	55.3941785

Table4. Best results for unknown parameters, I. SSE, V. SSE, P. time of SCA compared to ABC and SSA.

	ABC	SSA	SCA
$\xi 1$	-0.99922941	-1.10413427	-1.06812358
$\xi 2$	0.003004061	0.003375469	0.00354224
$\xi 3$*10-5	6.158490340	6.717765091	8.73639333
$\xi 4$	-0.000188466	-0.00019655	-0.00019156
λ	17.21429614	20.48342548	23.36054644
Rc	0.000602621	0.000172526	0.000560381
b	0.018008166	0.021990350	0.024833032
I. SSE	0.363087479	0.259670744	0.508065511
V. SSE	0.154466671	0.233406900	**0.119314180**
P. time	4.281250000	2.437500000	**0.921875000**

From the results in table 3 and 4, SCA has minimum sum square error than the other algorithms for last comparison and consumed the little processing time due to its simplicity during exploration the parameters search space. However, ABC has best minimum sum square error for the identification case. SCA has good performance based on the models' data sets used. Convergence curve of fitness for identification case is represents in fig. 4. It clarifies that SCA ability to explore optimal solution during the search space. PEMFC polarization curves and calculated voltage obtained based on the extracted parameters and data sets are represented in fig 2, 3.

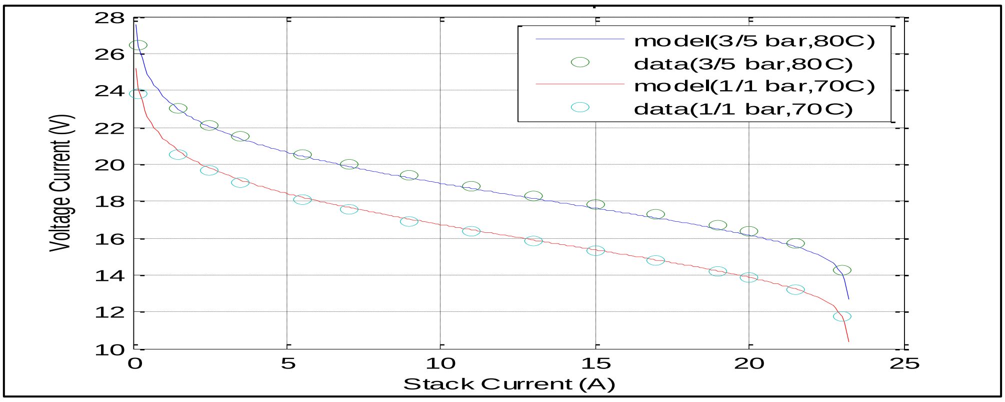

Fig 2. Identification case of SCA

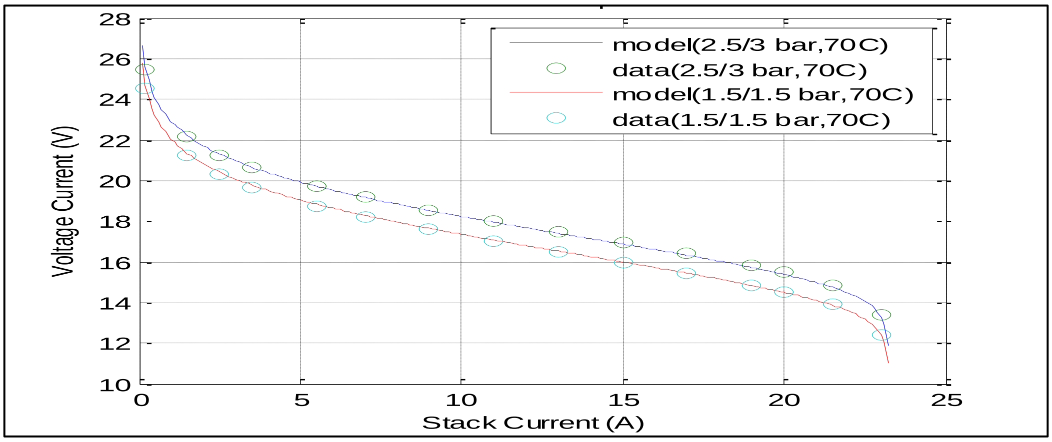

Fig3. Validation case of SCA

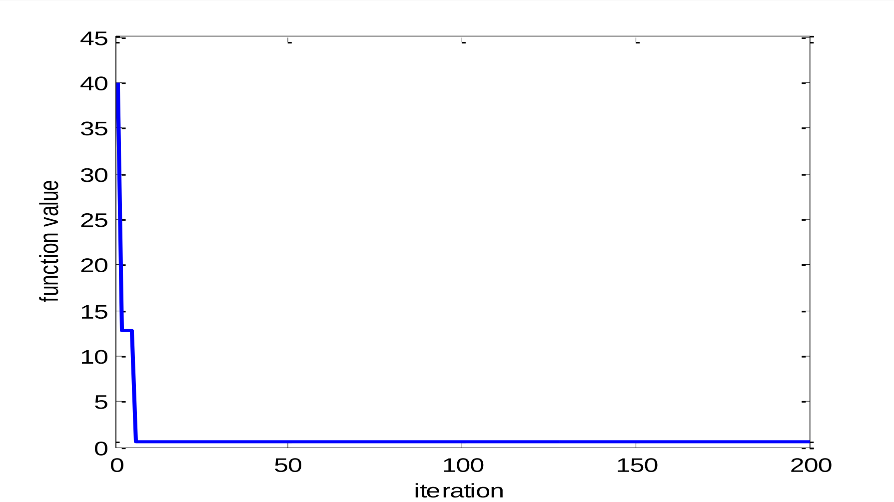

Fig 4. Convergence curve of SCA for PEMFC

5. CONCLUSION

According to the results of this work, sine-cosine algorithms obtain good estimation for polymer electrolyte membrane fuel cell. It closes the model performance to actual stack. SCA has a good ability for exploration the model parameters that can enhance the model efficiency, minimize the model error and produce more accurate results.

REFERENCES

1. Amphlett, J. C., Baumert, R. M., Mann, R. F., Peppley, B. A., Roberge, P. R., & Harris, T. J. (1995). Performance modeling of the Ballard Mark IV solid polymer electrolyte fuel cell I. Mechanistic model development. *Journal of the Electrochemical Society, 142*(1), 1-8.
2. Askarzadeh, A. (2013). Parameter estimation of fuel cell polarization curve using BMO algorithm. *international journal of hydrogen energy, 38*(35), 15405-15413.
3. Askarzadeh, A., & Rezazadeh, A. (2011). An innovative global harmony search algorithm for parameter identification of a PEM fuel cell model. *IEEE Transactions on industrial electronics, 59*(9), 3473-3480.
4. Corrêa, J. M., Farret, F. A., Canha, L. N., & Simoes, M. G. (2004). An electrochemical-based fuel-cell model suitable for electrical engineering automation approach. *IEEE Transactions on industrial electronics, 51*(5), 1103-1112.
5. Correa, J. M., Farret, F. A., Popov, V. A., & Simoes, M. G. (2005). Sensitivity analysis of the modeling parameters used in simulation of proton exchange membrane fuel cells. *IEEE Transactions on energy conversion, 20*(1), 211-218.
6. Karaboga, D., & Basturk, B. (2007). A powerful and efficient algorithm for numerical function optimization: artificial bee colony (ABC) algorithm. *Journal of global optimization, 39*(3), 459-471.
7. Mendes, R., Kennedy, J., & Neves, J. (2004). The fully informed particle swarm: simpler, maybe better. *IEEE Transactions on Evolutionary Computation, 8*(3), 204-210.
8. Mirjalili, S. (2016). SCA: a sine cosine algorithm for solving optimization problems. *Knowledge-Based Systems, 96*, 120-133.
9. Mirjalili, S., Gandomi, A. H., Mirjalili, S. Z., Saremi, S., Faris, H., & Mirjalili, S. M. (2017). Salp Swarm Algorithm: A bio-inspired optimizer for engineering design problems. *Advances in Engineering Software, 114*, 163-191.
10. Mitchell, M. (1998). *An introduction to genetic algorithms*: MIT press.
11. Mo, Z. J., Zhu, X. J., Wei, L. Y., & Cao, G. Y. (2006). Parameter optimization for a PEMFC model with a hybrid genetic algorithm. *International Journal of Energy Research, 30*(8), 585-597.
12. Niu, Q., Zhang, L., & Li, K. (2014). A biogeography-based optimization algorithm with mutation strategies for model parameter estimation of solar and fuel cells. *Energy conversion and management, 86*, 1173-1185.
13. Saeed, E. W., & Warkozek, E. G. (2015). Modeling and analysis of renewable PEM fuel cell system. *Energy Procedia, 74*, 87-101.
14. Wang, Y., Chen, K. S., Mishler, J., Cho, S. C., & Adroher, X. C. (2011). A review of polymer electrolyte membrane fuel cells: Technology, applications, and needs on fundamental research. *Applied energy, 88*(4), 981-1007.
15. Yang, S., & Wang, N. (2012). A novel P systems based optimization algorithm for parameter estimation of proton exchange membrane fuel cell model. *international journal of hydrogen energy, 37*(10), 8465-8476.
16. Ye, M., Wang, X., & Xu, Y. (2009). Parameter identification for proton exchange membrane fuel cell model using particle swarm optimization. *international journal of hydrogen energy, 34*(2), 981-989.
17. Zhang, L., & Wang, N. (2013). An adaptive RNA genetic algorithm for modeling of proton exchange membrane fuel cells. *international journal of hydrogen energy, 38*(1), 219-228.