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Article

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Energy Reports

Provided in Cooperation with:

Elsevier

Suggested Citation: Guo, Haibing; Tao, Hai; Salih, Sinan Q.; Yaseen, Zaher Mundher (2020) : Optimized parameter estimation of a PEMFC model based on improved Grass Fibrous Root Optimization Algorithm, Energy Reports, ISSN 2352-4847, Elsevier, Amsterdam, Vol. 6, pp. 1510-1519, <https://doi.org/10.1016/j.egy.2020.06.001>

This Version is available at:

<https://hdl.handle.net/10419/244140>

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Research paper

Optimized parameter estimation of a PEMFC model based on improved Grass Fibrous Root Optimization Algorithm

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ARTICLE INFO

Article history:

Received 3 March 2020

Received in revised form 3 May 2020

Accepted 1 June 2020

Available online 8 June 2020

Keywords:

Polymer membrane fuel cell

Electrochemically–mechanically model

Parameter identification

Grass Fibrous Root Optimization Algorithm

Sensitivity analysis

ABSTRACT

This paper presents a new optimal methodology for parameter identification of a 50 kW polymer membrane fuel cell (PEMFC) based on the economical–functional model. The objective of the study is to optimal estimation of the system parameters such that the minimum total cost has been needed for the stack construction. The total cost here is the sum of the fuel cell stack cost and its auxiliaries by considering air and hydrogen stoichiometric coefficient, system pressure, the current density, and the system temperature. For solving the minimization problem, a newly modified model of the Grass Fibrous Root Optimization Algorithm (MGRA) has been presented. Final results are compared with some several well-known algorithms to indicate the system efficiency and the reliability of the system toward different parameters has been indicated by applying sensitivity analysis.

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1. Introduction

Energy is a key pillar of growth and improvement in the world such that energy consumption and minimization of losses can be considered as an indicator for measuring the development of a country (Aghajani and Ghadimi, 2018; Liu et al., 2017). The use and supply of energy is of fundamental importance to a community and has the greatest impact on the environment due to the large scale and the pervasive nature of energy in various activities. Generation, transmission, distribution, and energy consumption affect the environment during various stages from extraction of primary resources to delivery of services and end-use (Gollou and Ghadimi, 2017). The issue of energy and the environment is necessity for sustainable development (Zhou et al., 2020; Bejan, 2020).

Fossil fuel resources are limited and, with optimistic assumptions, they will be completed in the next 70 to 150 years (Hosseini Firouz and Ghadimi, 2016). It is anticipated that in the next two decades, the need for fossil fuels will exceed its production and thus threaten a global energy shortage crisis. In this regard, it is expected that hydrogen–fuelled internal combustion engines will be used in the medium term and fuel cells will first be used in hybrid power systems and then in the long run in hydrogen power systems (Hamian et al., 2018). Fuel cell is an advanced,

sustainable, clean and biocompatible power system for the future. The use of hydrogen in conjunction with the development of fuel cells has provided a very clear vision for the future for the energy sector and internationally (Wang et al., 2018).

Fuel cell directly converts the chemical energy into the electricity. Unlike batteries which, due to the limited amount of reactive material in the battery tank, cannot supply the required energy after a while, the reactant material is continuously pumped into the fuel cell and the products are discharged continuously, thus a fuel cell can work continuously (Leng et al., 2018; Fan et al., 2020). It is also highly efficient because it converts energy directly. In the fuel cell, hydrogen gas has been employed as fuel and is produced by its reaction with oxygen, in addition to electrical energy, water and heat (Gong and razmjooy, 2020; Akbary et al., 2019). In other words, in this conversion, the reverse of the water electrolysis reaction occurs. Fuel cells have advantages such as cleanliness, silent operation, lack of greenhouse gas emissions, lack of moving components, and easy connection to microturbines (Mir et al., 2020; Yin and Razmjooy, 2020; Yu and Ghadimi, 2019).

The polymer membrane fuel cell (PEMFC) due to its low operating temperatures, high operating density, low weight and susceptibility to price reductions is of great importance and can be used more effectively from the other fuel cells in transport applications (Ebrahimian et al., 2018). The PEMFC is one of the most widely used fuel cells at various power levels, first designed for use in NASA's spacecraft. In this type of fuel cell, Nafion is used

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as electrolyte and hydrogen as fuel (Khodaei et al., 2018). Their operating temperature is around 70 °C–80 °C, which is the reason for the use of expensive catalysts such as platinum for rapid electrochemical reactions. One of the most important advantages of this type of fuel cell is its low start-up time, high power density as well as low operating temperature. While its electrolyte is highly sensitive to carbon monoxide, even a small amount of it can cause membrane poisoning. Recently, fuel cell parameter identification has attracted the attention of many researchers and scientists in the technology and many functional and economical models have been developed. The PEMFC model identification is usually performed for achieving two substantial purposes: to estimate the fuel cell efficiency and to explore the PEMFC. The first mathematical model of the PEMFC was introduced in 1992 and the results proved well agreement with the empirical data (Bernardi and Verbrugge, 1992).

Bagal et al. (2018) proposed a numerical methodology for performance evaluation of a PEMFC. The analysis was applied to show the correlations among gas diffusion layers, fuel cell performance, and material characteristics.

In 2017, another modeling based on fractional theory was proposed for parameter identification of a PEMFC (Gheydi et al., 2016). The results approved that the achieved values by the presented technique give appropriate results.

Another numerical work was proposed by Firouz and Ghadimi (2016) for the PEMFCs stack modeling. Then, ARX and ARMAX validation were adopted for verifying the method modality. They also used PI and PID controllers for achieving a desired load current.

Eslami et al. (2019) proposed a method for parameters estimation of a 3 kW PEMFC stack. The method is based on a quasi-dynamic parameters model. The study utilized a hybrid version of particle swarm optimization (PSO) algorithm and genetic algorithm (GA) to decrease the risks of being trapped into local optimum. The results showed a good agreement between the proposed model and the empirical data. The study finally simulated current injection into the model under different conditions, and the comparison of the results and the experimental data based on fast Fourier transform were analyzed. Hanning window was also used for reducing the spectral leakage error.

As can be concluded from the above literature, several types of classic methods are presented for parameter identification of the fuel cells. A big problem of classic methods is that due to the physical consideration of the fuel cells by the classic methods, the model complexity is increased that makes it so hard to find a proper solution for the problem. Recently, the use of metaheuristic algorithms for modeling of the PEMFC parameters are exponentially increasing (Saeedi et al., 2019; Ye et al., 2020; Cao et al., 2019), for example, Improved Butterfly Optimization Algorithm (Zhi et al., 2019), backtracking search algorithm (Khan et al., 2018), Whale Optimization Algorithm (El-Fergany et al., 2019), and Multi-verse optimizer (Fathy and Rezk, 2018).

Ye et al. (2020) introduced a modified metaheuristic technique based on seagull optimization algorithm for optimal model parameter identification of a PEMFC stack. The optimized model was then analyzed based on two practical PEMFC case studies and final results were compared with some metaheuristics to show the performance of the algorithm.

Ebrahimian et al. (2018) studied on a PEMFC model identifier based on optimized neural network. The method was based on Elman neural network. To decrease the error value and escaping from the local minimum value for the error, a hybrid metaheuristic technique based on World Cup Optimization (WCO) and Fluid Search Optimization (FSO) algorithms was adopted. Final achievements showed the superiority of the method toward the compared techniques. Due to the high complexity of the

PEMFCs, metaheuristic techniques give better results because of their well ability to escape from the local minimum toward the classic methods (Razmjoooy et al., 2016; Razmjoooy and Ramezani, 2014; Namadchian et al., 2016). The present study proposes a new model estimation of a PEMFC, such that the parameters of the model have been optimized based on a modified model of Grass Fibrous Root Optimization Algorithm (MGRA). The main contribution of the paper is as follows:

- Optimal method is used to minimize the total cost of a 50-kW PEMFC stack.
- Functional-economic model is used for mathematical modeling.
- Minimization is applied based on a newly modified metaheuristic.
- The new metaheuristic is based on Grass Fibrous Root Optimization Algorithm.
- Final results were compared with some other well-known algorithms.
- To show system reliability, sensitivity analysis has been applied to the system parameters.

2. The system overview

Fig. 1 shows the general arrangement of the proposed system. The analyzed system is a 50 kW PEMFC stack that is popular in different remote and portable applications such as remote power plants, vehicles, space equipment, military usages, and combined heat and power generation systems. Based on Fig. 1, after entering air into the PEMFC stack, it moves to the compressor to increase its pressure to send over humidifiers and then pumps and electrical control devices. The main objective of PEMFC system optimization in this study is to achieve optimal values for the volume of air and hydrogen entering the system, system pressure parameters, the operating temperature of the system as well as the current flow density for the least possible cost to the system.

3. Mathematical modeling of the system

The key idea in the present research is minimizing the total cost of the system containing investment cost (C_{in}) and operating cost (C_t) regards to the discount rate (R_d), i.e.

$$\min C = C_{in} + \sum_{t=1}^n \frac{C_t}{(1 + R_d)^t} \quad (1)$$

where, the investment cost for the PEMFC stack contains auxiliary cost (C_{aux}), the stack cost (C_{stack}), the fuel cost (C_{fuel}), and the storage tank cost (C_{st}), i.e.

$$C_{in} = C_{st} + C_{stack} + C_{fuel} + C_{aux} \quad (2)$$

The PEMFC stack contains several elements that effect on its total cost. For example, bipolar surfaces, ion exchange membranes, electrodes, gaskets, end plates, and screws.

By considering the assumption that all the input fuel has been consumed, the fuel cost has been formulated by the following:

$$C_{fuel} = C_{H_2} \times P_{stack} \times \eta_{stack}^{-1} \times H_2^{TV-1} \quad (3)$$

where, C_{H_2} represents the cost of each kilogram of H_2 , P_{stack} describes the power of fuel cell, η stands for the stack efficiency, and H_2^{TV-1} describes the hydrogen thermal value (kJ/kg). Fig. 2 shows the schematic of a PEMFC.

The total cost of the PEMFC stack based on (Grujicic and Chittajallu, 2004) can be achieved by the following.

$$C_{stack} = \left(C_{mo} + \frac{C_{PEM} + C_E + C_{BP} + C_{Pt} + C_{Aux}}{10 \times V_t \times i} \right) \quad (4)$$

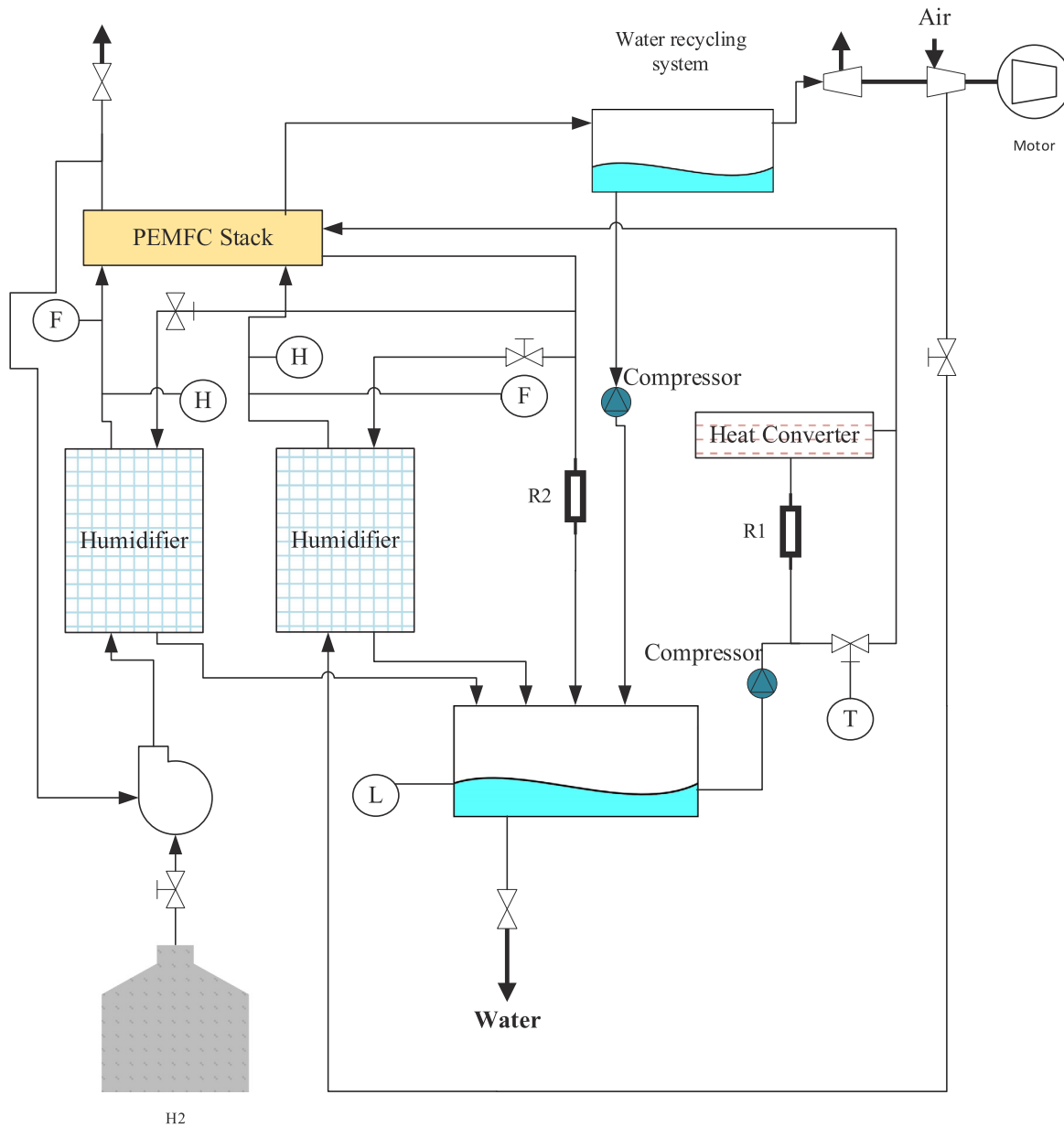


Fig. 1. The system arrangement in the present study.

where, C_{stack} is the total cost of the PEMFC (\$/kW), C_{mo} describes the stack montage cost (\$/kW), C_{PEM} stands for the PEMFC membrane cost (\$/m²), c_E describes the electrode cost (\$/m²), c_{BP} represents the bipolar plates cost (\$/m²), c_{Aux} represents the auxiliaries cost (\$/m²), V_t describes the terminal voltage of PEMFC (v), i determines the cell density (A/m²), and c_{Pt} is the platinum cost utilized in the membrane (\$/m²) and is obtained as follows:

$$c_{Pt} = M_{Ct} \times C_{pt}^{kg} \quad (5)$$

where, C_{pt}^{kg} represents the cost for each kilogram of platinum (\$/kg) and M_{Ct} describes the utilized volume of the catalyst (kg/m²).

The auxiliary cost for the system contains a part of the PEMFC stack cost and the fuel storage cost. This portion includes the cost of different auxiliary equipment such as humidifier, compressor, electrical control equipment. Based on (Mahmoudi et al., 2019), the auxiliary cost can be formulated by the following equation:

$$C_{Aux} = 0.51\eta_{FC} \times (C_{st} + C_{stack}) \quad (6)$$

The simulation is based on 90-months time period of power generation without considering the production time of the PEMFC stack (Mahmoudi et al., 2019), so this value is achieved as follows:

$$C_{st} = (1 + R_i)^{t-1} C_{in} + 3600 \times (1 - R_{if}^t)^{t-1} \times C_{H_2} \times \frac{t_0 \times c_f \times \lambda_{H_2}}{6480 \times V_t \times i} \quad (7)$$

where, λ_{H_2} describes the hydrogen stoichiometric coefficient, t_0 represents the functional lifetime of the fuel cell, and R_i and R_{if}^t describe the inflation ratio and fuel inflation ratio, respectively, and C_{H_2} illustrate the saturation of H₂ and is achieved as follows:

$$C_{H_2} = \frac{P_{H_2}}{1.1 \times 10^6} \times e^{\frac{-77}{\eta_{FC}}} \quad (8)$$

And the system efficiency is obtained by the following equation (Tsuchiya and Kobayashi, 2004):

$$\eta_{FC} = -\frac{V_t \times \mu_s}{1.25 \times P_{stack}} \times (P_{stack} - P_{aux}) \quad (9)$$

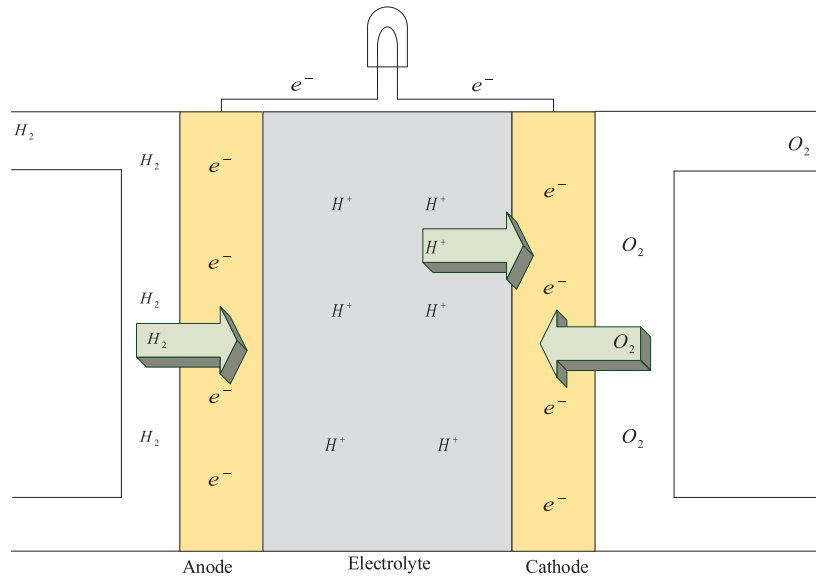


Fig. 2. The comprehensive model of a PEMFC.

where, μ_s stands for the inverse stoichiometric coefficient, P_{stack} represents the stack power (w), and P_{aux} describes the auxiliary components power (w), and the given constant 1.25 in denominator of the Eq. (8) is an empirical value (Ahadi et al., 2014).

The fuel cell voltage can be modeled as follows (Corrêa et al., 2004; Aouali et al., 2017):

$$V_t = N_{nc} \times (E_N - E_{ops} - E_{\Omega} - E_{op}) \quad (10)$$

where, N_{nc} stands for the number of connected cells, E_N determines the Nernst equation, E_{ops} describes the over-potential saturation, E_{Ω} represents the Ohmic voltage drop, and E_{op} represents the activation over-potential of each cell.

In the above equation, the Nernst relation of the PEMFC is achieved by the following (Kandidayeni et al., 2019):

$$E_N = 1.23 - 8.5 \times 10^{-4} (T_{FC} - 298.15) + 4.31 \times 10^{-5} \times T_{FC} \times [\ln(P_{H_2}) + 0.5 \times \ln(P_{O_2})] \quad (11)$$

where,

$$P_{O_2} = R_{hc} \times P_{H_2O} \left[\frac{1}{\frac{R_{hc} \times P_{H_2O}}{P_c} \times e^{\frac{1.635 I_{FC} / A}{T^{1.334} I_{FC}}}} - 1 \right] \quad (12)$$

$$P_{H_2} = \frac{R_{ha} \times P_{H_2O}}{2} \left[\frac{1}{\frac{R_{ha} \times P_{H_2O}}{P_a} \times e^{\frac{1.635 I_{FC} / A}{T^{1.334} I_{FC}}}} - 1 \right] \quad (13)$$

where, A stands for the active area of the membrane, I_{FC} represents the operating current of the fuel cell, P_a and P_c determine the input partial pressures of anode and cathode, respectively, P_H , P_{O_2} , and P_{H_2O} determine the partial pressure for H_2 , O_2 and H_2O , respectively and R_{ha} and R_{hc} determine electrodes of anode and cathode, respectively. The saturation vapor pressure for the PEMFC is defined by P_{H_2O} , and achieved by the following (Tizhoosh, 2005):

$$\log_{10}(P_{H_2O}) = 0.0295 \times (T_{FC} - 273.15) - 2.18 - 9.18 \times 10^{-5} T_c^2 + 1.4 \times 10^{-7} T_c^3 \quad (14)$$

where, T_{FC} represents the operating cell temperature ($^{\circ}C$).

The voltage of over-potential saturation (E_{ops}) is given in the following (Ye et al., 2020):

$$E_{ops} = -\beta \times \ln \left(J_{max} - \frac{J}{J_{max}} \right) \quad (15)$$

where, β stands for a parametric coefficient, and J and J_{max} describe the standard and the maximum current densities, respectively. The activation over-potential loss can be achieved as follows:

$$E_{op} = -[\gamma_1 + \gamma_2 \times T_{FC} + \gamma_3 \times T_{FC} \times \ln(C_{O_2}) + \gamma_4 \times T_{FC} \times \ln(I_{FC})] \quad (16)$$

where, C_{O_2} describes the saturation of O_2 in the catalytic interface of the cathode (mol/cm^3) and is achieved as follows:

$$C_{O_2} = \frac{P_{O_2}}{5.1 \times 10^6} \times e^{\frac{498}{T_{FC}}} \quad (17)$$

where,

$$\gamma_2 = 2.9 \times 10^{-3} + 2.1 \times 10^{-4} \ln(A) + 4.3 \times 10^{-5} \ln(C_{H_2}) \quad (18)$$

The Ohmic voltage drop can be formulated as follows:

$$E_{\Omega} = I_{FC} \times (R_c + R_m) \quad (19)$$

where, R_c describes the connection resistance and R_m is membrane resistance and is achieved as follows:

$$R_m = \frac{1}{S} \times \rho_m \times l \quad (20)$$

$$\rho_m = \frac{181.6 \times \left[1 + 0.062 \left(\frac{T_{FC}}{303} \right)^2 \times \left(\frac{I_{FC}}{S} \right)^{2.5} + 0.03 \left(\frac{I_{FC}}{S} \right) \right]}{\left[\lambda - 0.063 - 3 \left(\frac{I_{FC}}{S} \right) \right] \times e^{\frac{T_{FC}-303}{T_{FC}}}} \quad (21)$$

where, I_{FC} describes the operating current of PEMFC (A), l stands for the thickness of the membrane (cm^2), S represents the surface for membrane (cm^2), β_i describes the empirical coefficients, λ determines the controlling parameter, ρ_m describes the resistivity of the membrane. The optimal value for the parameters based on (Ye et al., 2020) is as follows: $\beta = 0.01$, $\gamma_1 = -1.03$, $\gamma_2 = 3.48e-3$, $\gamma_3 = 7.79e-5$, $\gamma_4 = -9.48e-5$, $R_c = 1.63e-4$, and $\lambda = 15.04$.

In addition to achieve the efficiency of the PEMFC stack, the power of the auxiliary components should be also calculated. The

Table 1
The system constraints.

Parameter	Minimum	Maximum
λ_{air}	1	3
λ_{H_2}	1	3
P_{sys}	0.13	0.50
i	0	1
T	60	90

additional power supply for the 50 kW power generation based on (Na and Gou, 2007) is considered 5.2 kW.

$$P_{com} = C_p \times \frac{T_{in}}{\eta_m \eta_{mt}} \left(\left(\frac{P_{sys}}{P_{in}} \right)^{0.26} - 1 \right) \times \dot{m} \quad (22)$$

where, T_{in} describes the temperature for the input air ($^{\circ}\text{C}$), P_{in} is the input pressures (atm), P_{sys} represents the system pressures (atm) and:

$$\dot{m} = 3.57e-7 \times \lambda_{air} \times i \times A \times N \quad (23)$$

The fuel storage cost as another investment term can be considered as follows:

$$C_{st} = \frac{C_s 1}{A \times F \times V_t} \quad (24)$$

where, t stands the time for PEMFC efficiency (9 month/year), F represents the Faraday constant, A describes area of the cell (m^2), and C_s is the storage cost per kilogram for hydrogen which is defined by the hydrogen volume as follows:

$$C_s = \begin{cases} 5.244 \text{ \$/kg for } 27 \text{ 000 kg} \\ 1.752 \text{ \$/kg for } 276 \text{ 000 kg} \\ 1.044 \text{ \$/kg for } 27 \text{ 600 000 kg} \end{cases} \quad (25)$$

The system operating temperature is for protecting of both water vapor and its high temperature and to protect the membrane breaking. This is done by considering the high level as 90°C and low level as 60°C . The other constraints for the optimization are given in Table 1 (Na and Gou, 2007).

4. Improved grass fibrous root optimization algorithm

The parameter identification of a PEMFC is too important for designing, monitoring, and manufacturing. In most cases, its sensitive applications lead the researches to have more attention to this subject. Having more information about the PEMFC parameters makes a significant help to analyze its efficiency during the process. Yet, there are lots of different methods for parameter identification of the PEMFCs that are categorized into two classes, classic methods and metaheuristics. Classic methods are exact methods for solving the problems but they have some significant drawbacks. For instance, they have high computational cost such that they lose their performance in the complicated and high-dimension problems. the classic methods also sometimes stuck in the local optimum solution. In most cases, the parameter estimation methods are based on iteration to speed up the process for on-line applications. These reasons lead the researcher to study on a kind of iterative random methods called metaheuristics to cover and resolve the mentioned shortcomings. Metaheuristics are sort of optimization techniques that usually inspired by the nature, for instance quantum invasive weed optimization (QIWO) (Razmjoooy and Ramezani, 2014), Emperor Penguin Optimizer (EPO) (Dhiman and Kumar, 2018), pigeon-inspired optimization algorithm (Cui et al., 2019), world cup optimization (WCO) (Bandaghipri et al., 2016; Razmjoooy et al., 2017; Shahrezaee, 2017; Tian et al., 2020), states of matter search (SMS) (Cuevas et al., 2018), and Grass Fibrous Root Optimization

Algorithm (GRA) (Akkar and Mahdi, 2017). The GRA is a new metaheuristic technique that is introduced by Akkar and Mahdi that Akkar and Mahdi (2017). This technique is an optimization algorithm inspired by the grass plants regeneration, evolution, and their fibrous root system. These plants are essentially simulated during two mechanisms including the underground stems that is often performed underground by sending out roots and shooting the nodes, called rhizomes and the second mechanism is based on the stems that raise below the surface. The root has been employed for local and the global exploration of the water and other mineral resources. The mentioned mechanisms are adopted to model the optimal searching of the GRA. In the following, the mathematical model of GRA has been introduced.

4.1. Basic grass fibrous root optimization algorithm

The GRA is a population-based algorithm. The agents of this algorithm are called grass swarms that are generated randomly and uniformly in the search space initiated in seeding process (pop). During optimization, the population is regenerated (Pop_{New}) bounded between Pop_{New}^L and Pop_{New}^H as lower and upper bounds. By considering the best value (G_{best}) as follows:

$$G_{best} = \min(f(\text{swarm})) \quad (26)$$

where, f describes the mean square error (MSE) function.

The number of grasses (N_{Gr}) is another term which is modeled by stolons that are often deviated by the basic grass (N_{Gr}^N) contains a step size less than Pop_{New}^H by the following:

$$N_{Gr} = \left\| \frac{pop}{2} \times \left(\frac{avg(MSE)}{avg(MSE) + min(MSE)} \right) \right\| \quad (27)$$

where, min and avg describe the minimum value and the average value, respectively.

The maximum value of the new produced grass branches ($0.5 \times pop$) gives minimum value of MSE. Another term for modeling the algorithm is the new grass ($pop - N_{Gr} - 1$) which is extracted randomly from the survived best grasses (S_{de}). New extracted branch grasses by the G_{best} by the following equation:

$$Gr_N = ones(N_{Gr}, 1) \times G_{best} + 2 \times \max(Pop_{New}^H) \times (\sigma(N_{Gr}, 1) - 0.5) \times G_{best} \quad (28)$$

where,

$$S_{de} = Gr_N + \alpha \times \max(Pop_{New}^H) \times (\sigma(pop - N_{Gr} - 1, 1) - 0.5) \times Pop_{New}^H \quad (29)$$

where, α is a fixed value equal to 2, $ones(\cdot)$ stands for the one's column vector, $\sigma \in [0, 1]$ describes a random value, and Gr_N describes the ($pop - Gr - 1$) highest MSE initial population.

And the new population is considered by the following:

$$Pop_{RG} = [G_{best}; Gr_N; S_{de}] \quad (30)$$

The new regenerated population (Pop_{RG}) is calculated for achieving the minimum value of MSE grass. If new G_{best} has better results than its earlier iteration, it will be substituted by the best new grass (solution), if not so, the absolute rate of decrease in MSE should be calculated. In the event that the rate has less than or equal to a predetermined tolerance value (ϵ), a global stack ($stack_g$) has been increased until reach its maximum value. In this situation, the next local search starts as follows:

$$M = \min_{i=1, \dots, pop} (MSE) \quad (31)$$

$$best_{min} = \min_{j=1, \dots, iter} (M) \quad (32)$$

$$\left| \frac{\min_{i=1, \dots, pop} (MSE) - G_{best}}{\min_{i=1, \dots, pop} (MSE)} \right| \leq \epsilon \quad (33)$$

The term secondary roots can be determined by random numbers with d number of hair roots. For updating the hair root location,

$$G_{best}^m(1, i) = Avg(G_{best}) + G_{best}(1, i) + C_2 \times (\sigma - 0.5) \quad (34)$$

$$C = [C_1, C_2, \dots, C_{10}] \quad (35)$$

$$C_2 = C \times (1 + (\|\sigma \times 10\|)) \quad (36)$$

$$i = 1, 2, \dots, d, k = 1, 2, \dots, S$$

where, S describes the number of secondary generated roots, G_{best}^m represents the modified local G_{best} , C stands for the investigated step size vector equation, and C_2 is a random element of C .

If G_{best}^m has a value less than G_{best} , it will be substituted by it, else, MSE absolute rate of decreasing should be calculated. In the event that the rate gives a value less than ε , then the local stack counter ($stack_i$) will add one plus, if $stack_i$ reached to the maximum value of itself, the hair root loop should be stopped and a new secondary root loop should be started.

4.2. Modified grass fibrous root optimization algorithm

Although the grass fibrous root optimization algorithm (GRA) as one of the newest algorithms gives satisfying solution for the optimization problems, it sometimes stuck in the local optimum. This shortcoming gives a solution with premature convergence for the problem. In the present research, two mechanisms have been employed to resolve this shortcoming as it is possible.

Although, due to the random initialization of the grass plants, GRA has high population diversity, during updating, the difference of grass population has been decreased that consequently decrease the diversity of the algorithm that results a solution with local optimum and premature convergence. To resolve this problem, mutation mechanism is added to the algorithm to resolve the problem. This mechanism improves combines the advantages of basic GRA and the evolutionary algorithm for increasing the searching performance. By considering the diversity of GRA as follows:

$$D = \frac{1}{n \times L} \times \sum_{j=1}^n \sqrt{(f(swarm)_i - \bar{f}(swarm)_i)^2} \quad (37)$$

where, L describes the length of the longest diagonal line in the solution space and $\bar{f}(swarm)_i$ represents the mean value of $f(swarm)_i$ as the cost value of the i th individual.

The population will be kept in high diversity if $D < D_{low}$. By adopting the mutation coefficient to the algorithm, the updated new extracted branch grasses can be considered as follows:

$$Pop_{New} = Pop_{New} + \varphi \times \sigma \times \tau \quad (38)$$

$$G_{best} = G_{best} + \varphi \times \sigma \times \tau \quad (39)$$

where, σ represents a stated parameter, $\tau \sim N(0, 1)$, $\varphi \geq 10 \times D_{low}$ is defined to meet $D < D_{low}$ after adopting the mutation. In this study, anti-cosine mechanism is applied to α to enhance the self-learning ability of the S_{de} as follows:

$$\alpha = Pop_{low} + (1 + Pop_{high} - Pop_{low}) \times \left(1 - \arccos \left(\frac{(-2 \times \frac{N_{it}}{I_{tmax}} + 1)}{\pi} \right) \right) \times \alpha \quad (40)$$

where, Pop_{low} and Pop_{high} describe the lower value and the higher value of the population, respectively, N_{it} describes the number of iterations and I_{tmax} stands for the maximum iterations value.

Fig. 3 gives the diagram flowchart of the proposed MGRA.

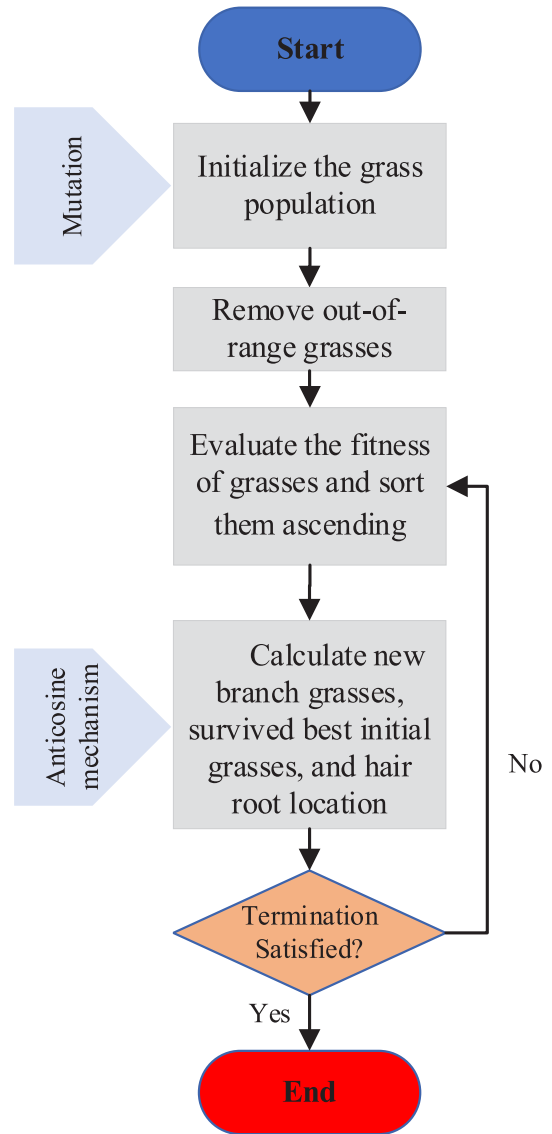


Fig. 3. The diagram flowchart of the proposed MGRA.

4.3. Algorithm validation

After designing a metaheuristic, it should be validated by some test functions to show its ability in optimization. In this study, 5 test functions including unimodal and multimodal functions are adopted for analyzing the algorithm efficiency. After the analyzing, it is also compared with some well-known algorithms including Deer Hunting Optimization Algorithm (DHO) (Brammya et al., 2019), Owl search algorithm (OSA) (Jain et al., 2018), Chaotic fruit fly optimization algorithm (CFA) (Mitić et al., 2015), Moth search algorithm (MSA) (Wang, 2018) to show its higher efficiency. Table 2 illustrates the over-all information of the test functions for validation. During the optimization, for all the algorithms, the population size is considered 100, and the stopping criteria is considered based on the maximum number of achieved functions.

To show a comparison among the algorithms, different values including “Median” as the median value of the test function, “std” as the standard deviation, and “minimum” and “maximum” as the minimum and maximum cost values for the algorithms, respectively have been employed.

Table 2
Over-all information of the employed test functions for validation.

Model	Function	Formulation	Optimal
Unimodal	Rotated high conditioned elliptic	$F_1(x) = f_1(M(x - o_1)) + F_1^*$	100
	Rotated Bent Cigar	$F_2(x) = f_2(M(x - o_2)) + F_2^*$	200
	Rotated discuss	$F_3(x) = f_3(M(x - o_3)) + F_3^*$	300
Multimodal	Shifted and rotated Rosenbrock	$F_4(x) = f_4 \left[M \left[\frac{2.048(x-o_4)}{100} \right] + 1 \right] + F_4^*$	400
	Shifted and rotated Ackley	$F_5(x) = f_5(M(x - o_5)) + F_5^*$	500

Table 3
Comparative results of the algorithms.

		MGRA	DHO (Brammya et al., 2019)	OSA (Jain et al., 2018)	CFA (Mitić et al., 2015)	MSA (Wang, 2018)
F_1	Maximum	4.85E+06	6.85E+07	6.74E+06	5.82E+06	7.42E+05
	Minimum	3.56E+05	9.16E+06	8.25E+05	1.42E+05	5.31E+04
	Median	3.61E+05	1.34E+07	2.35E+06	4.75E+05	3.41E+05
	std	1.93E+06	4.16E+07	5.80E+05	2.16E+05	1.62E+05
F_2	Maximum	3.14E+03	8.64E+06	4.37E+04	6.19E+03	1.58E+03
	Minimum	15.40E+02	3.62E+06	6.24E+03	3.53E+02	2.58E+02
	Median	10.53E+02	5.37E+06	2.83E+04	5.28E+02	2.41E+02
	std	2.48E+02	2.59E+06	7.34E+03	7.11E+02	2.53E+02
F_3	Maximum	6.85E+03	6.13E+04	5.92E+04	12.3E+03	1.35E+03
	Minimum	1.27E+03	1.99E+02	6.17E+03	4.73E+03	2.83E+02
	Median	4.64E+03	5.61E+03	4.51E+03	8.19E+03	3.57E+02
	std	5.17E+02	1.94E+04	4.13E+03	2.57E+04	1.48E+02
F_4	Maximum	8.36E+01	6.22E+02	7.54E+02	4.28E+02	1.85E+02
	Minimum	5.80E+01	4.31E+02	4.19E+02	1.14E+02	2.23E+02
	Median	6.29E+01	5.15E+02	6.64E+02	5.37E+02	2.14E+02
	std	5.13	3.43E+01	4.83E+01	2.76E+01	3.19E+01
F_5	Maximum	4.83E+01	4.89E+02	7.04E+02	6.39E+02	5.20E+02
	Minimum	4.65E+01	3.16E+02	2.45E+02	3.85E+02	5.20E+02
	Median	4.67E+01	3.95E+02	4.55E+02	4.46E+02	5.20E+02
	std	3.97E-04	5.17E-04	3.99E-03	4.18E-04	7.72E-05

As can be observed from Table 3, the minimum value for all five functions based on the suggested MGRA is the least. This indicates that the proposed algorithm has the highest precision with the minimum error among the compared methods. The other important index in Table 3 is that the standard deviation of the MGRA is the minimum. So, the proposed method has the highest robustness among the compared methods.

5. Simulation results

5.1. Optimal parameters calculation

The main objective is to minimize the fuel cell fabrication cost based on a new metaheuristic, called modified grass fibrous root optimization algorithm. Indeed, the optimization process is based on finding optimal parameter values for the PEMFC. The step wise procedure for the method is as follows:

- Start procedure
- $\min C = C_{in} + \sum_{t=1}^n \frac{C_t}{(1+R_d)^t}$
- Determine the optimal values for λ_{air} , λ_{H_2} , P_{sys} , i , T
- Return the solution

It is clear that the optimum operating temperature for the system is 75.6 °C, the optimum system pressure is 0.52 MPa, the optimum current density is about 0.57 mA/cm², and the optimal stoichiometry coefficients for air and hydrogen are 1.53 and 1.32, respectively. The results of the modified GRA have been also compared with basic GRA, OSA, and CFA to show its efficiency toward them (see Table 4).

The optimal cost for the proposed MGRA, basic GRA, OSA (Li et al., 2020), and CFA (Qin et al., 2018) are estimated at 0.0524 \$/kWh, 0.0648 \$/kWh, 0.1011 \$/kWh, and 0.1017 \$/kWh. Fig. 4 shows the total cost of system for the compared algorithms. The

Table 4
Optimal parameter selection for PEMFC based on four selected algorithms.

Algorithm	Parameter				
	λ_{air}	λ_{H_2}	P_{sys}	T	i
MGRA	1.53	1.32	0.52	75.6	0.57
GRA	1.45	1.26	0.44	74.1	0.60
OSA	1.12	1.05	0.14	74.2	0.33
CFA	1.35	1.18	0.38	68.5	0.55

results show that by increasing the number of iterations, the objective function moves to the minimum possible value.

To give more precise analysis of the method, sensitivity analysis has been adopted for the system. Here, variables are changed in each analysis, whereas, the other values get their optimal values that are obtained from MGRA.

5.2. The impact of pressure changes on the cell construction cost

Fig. 5 shows the effect of the system pressure variation on total cost. As can be seen, by enhancing the input system pressure, the total cost has been decreased, but growing the system pressure because of the physical and mechanical structure of the electrodes and the membrane, as well as the bipolar plates, is impossible which is because of the reason that membrane contains an ion exchange fuel which is too thin and over-pressed to break it.

By increasing the pressure, the linkages between the catalyst and the gas diffusion plates is eliminated, whereas the surfaces of gas diffusion commonly contain paper carbon or carbon coatings that are highly corrosive to the structure. Consequently, understanding the arrangement of its elements is tailored.

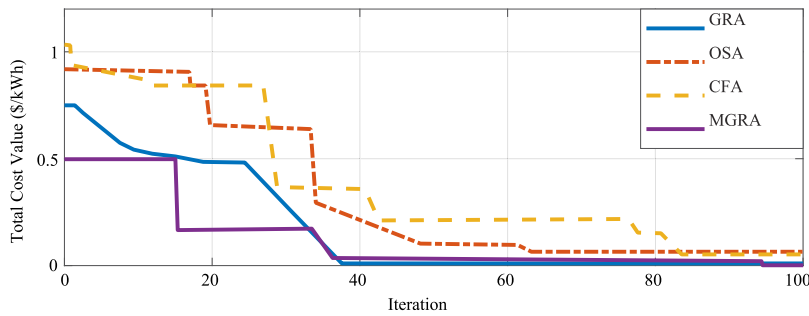


Fig. 4. The total cost of system for the compared algorithms.

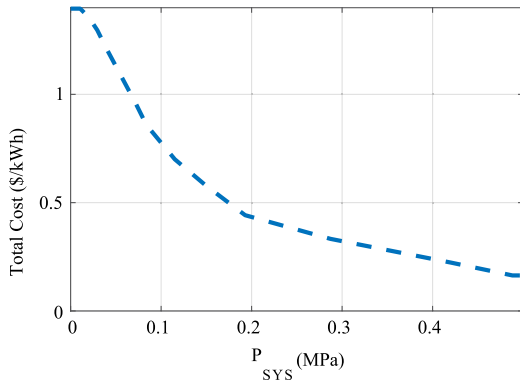


Fig. 5. The effect of the system pressure variation on total cost.

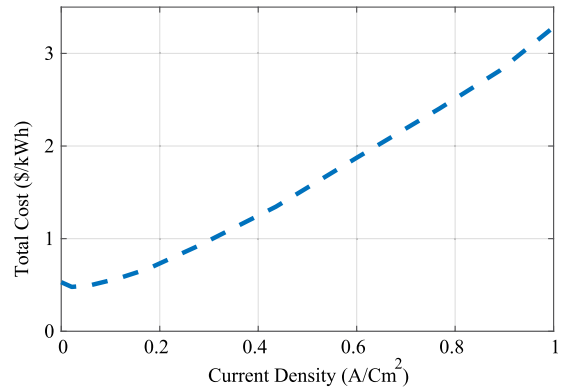


Fig. 7. The effect of the system current density variation on total cost.

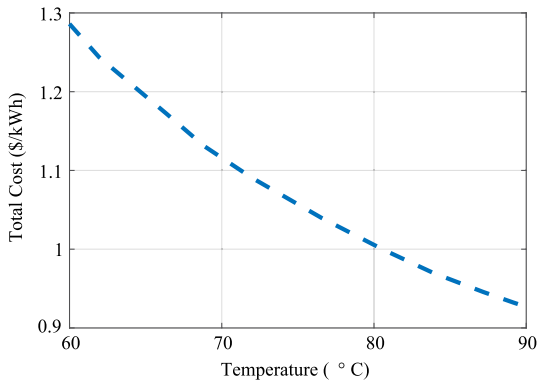


Fig. 6. The effect of the system temperature variation on total cost.

5.3. The effect of temperature variations on the total cost

In this subsection, we consider variant values for the operating temperature, while the other parameters of the fuel cell are fixed in their optimal values. As can be observed from Fig. 6, the total cost of the system has been reduced by temperature increasing. It is important to note that the heat resistance for the Nafion as a fuel cell membrane is a restrictive factor for the extremely high operating temperature. Also, the best time to move protons through the membrane is when the water is transferred in the two phases of the heater and operating fluid. During increasing the peak operating temperature value, the only water phase in the PEMFC is the steam phase that affects the hydrogen exchange which makes a significant decreasing in the system efficiency. This reason makes that in 75.6 °C, the passing water though the water is completely biphasic.

5.4. The impact of current density on the cell construction cost

Fig. 7 shows the effect of the system current density variation on total cost. As can be seen, because of the relationships in the model, the current density cannot be directly modified. But the results show that current density enhancement increases the cost of total system which is due to most significant ways to enhance the porosity of the porous membrane–catalyst–porous membrane current to do with relatively efficient methods during the membrane electrode assembly fabrication.

5.5. The effect of stoichiometric coefficients of air and hydrogen on the cell construction cost

Fig. 8 shows the effect of the system stoichiometric coefficients of air and hydrogen on total cost. As can be observed from the results, the total cost has been grown if the stoichiometry value has been increased. The stoichiometric ratio variations of the air have less impact than the hydrogen on the total cost. Thus, this ratio can be grown to get the best values of parameters with this restriction that due to increasing this ratio directly related to the input air to the compressor increasing, while the compressor power is a limiting factor for the total cost reduction.

Fig. 9 shows the effect of the system efficiency on the total cost. As can be observed, by enhancing the fuel cell system performance, its total cost is reduced.

6. Conclusions

This paper proposed an optimal method to minimize the total cost of a 50-kW polymer membrane fuel cell (PEMFC) stack and its auxiliaries like humidifiers and compressors. The model of the analyzed system was a functional-economic model such that all its elements are economically modeled. For solving the minimization problem, a newly modified version of Grass Fibrous Root

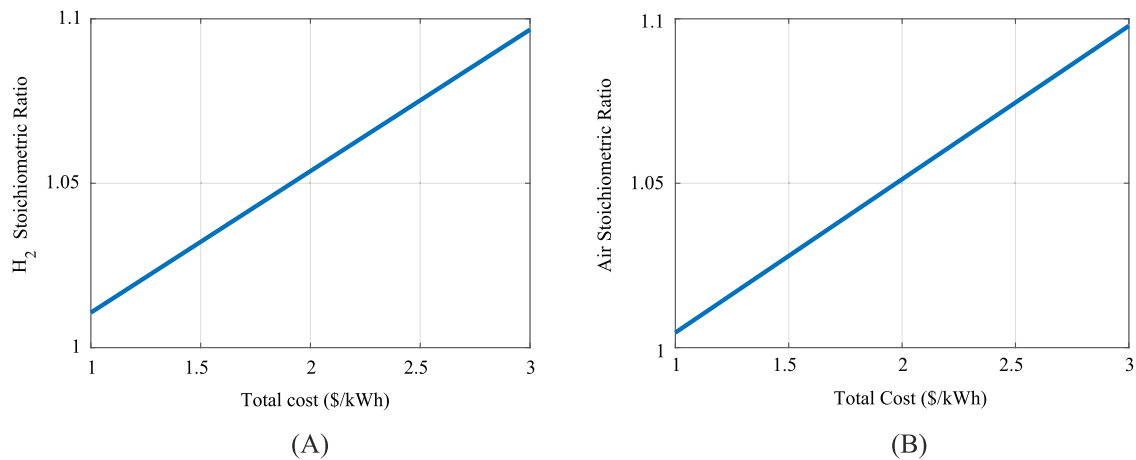


Fig. 8. The effect of the system stoichiometric coefficients of air and hydrogen on total cost.

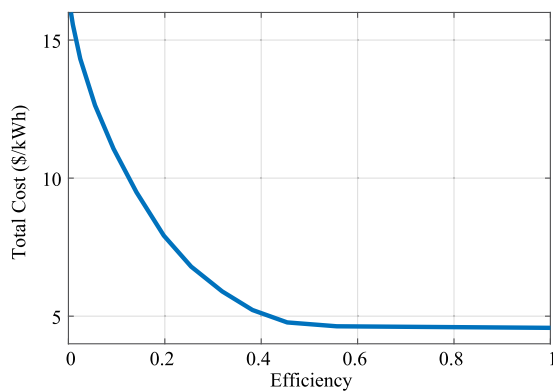


Fig. 9. The effect of the system efficiency on the total cost.

Optimization Algorithm (MGRA) was introduced. After designing the system, the optimal results were compared with some other well-known algorithms including OSA, CFA, and the basic GRA. The minimum value was achieved by the proposed MGRA with 0.0524 \$/kWh. Sensitivity analysis was then implemented on the proposed method by changing the parameters to show the reliability of the system against different variations. Final results showed the ability of the proposed methodology toward different variations.

CRedit authorship contribution statement

Haibing Guo: Investigation, Methodology, Writing. **Hai Tao:** Conceptualization, Data curation, Writing - original draft, Writing - review & editing. **Sinan Q. Salih:** Conceptualization, Data curation, Writing - original draft, Writing - review & editing. **Zaher Mundher Yaseen:** Conceptualization, Data curation, Writing - original draft, Writing - review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgment

Key Research and Development Program in Shaanxi Province (2020GY-078).

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