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Article

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Multi-objective optimization of a PEMFC based CCHP system by meta-heuristics

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ABSTRACT

This paper presents a multi-criteria economics, environment, and thermodynamics assessment for a combined cooling, heating, and power (CCHP) system consist of a heat recovery system, a small absorption chiller, a 5kW PEMFC stack, gas compressor, and a humidifier. This study presents an improved version of a new optimization technique called improved emperor penguin optimization (IEPO) algorithm for optimizing the system efficiency. After simulations, the system is analyzed in terms of energy and exergy efficiencies, annual cost, and pollutant emission reduction. Simulation results declare low operating temperature develop GHG emission reduction, high relative humidity, pressure of inlet gases, and system exergy performance. The results of the IEPO algorithm for showing the superiority of the algorithm.

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1. Introduction

Energy plays a special role in the economic growth, social welfare, improvement of the quality of life and security of a society. Global researches show that there is a direct relationship between a country's development and its energy consumption, and that is why developing countries have access to a variety of new energy sources to improve their economic status (Hosseini et al., 2013; Mehrpooya et al., 2019).

Electricity is one of the main factors underlying the growth and prosperity of the industrial, economic and social parts, so that one of the indicators of countries' evaluation and development is the index of capacity increase and distribution of electricity (Ghadimi, 2015; Ghadimi et al., 2017). In recent years, an awareness of the unprecedented increase in energy consumption and the unavoidable reality of fossil fuels have led to worldwide studies aimed at reducing energy consumption and reducing energy production costs, without Damage to the development process of countries is to be done. These studies have led to programs and strategies called "energy management" (Hosseini et al., 2014).

The overall definition of energy management can be the correct and efficient use of energy to achieve the most profit at the lowest cost to increase the competitive position in the market,

* Corresponding author. E-mail address: kittisak.j@chula.ac.th (K. Jermsittiparsert). which requires adjusting and optimizing energy consumption strategies, using systems and guidelines for reducing the amount of energy consumed per unit of production and reducing or keeping total production costs constant (Mehr et al., 2018). In this regard, the energy management functions of an economic organization can be summarized as follows:

- (1) Preparing a plan for optimizing energy consumption in different units and processes of the organization.
- (2) Reducing energy costs and energy losses without affecting the quantity and quality of the production.
- (3) Controlling the environmental impacts of energy production and consumption.

One of the solutions that energy policy makers around the world today use as an effective and efficient tool in energy management is to generate energy based on the co-generation method of electricity, heat and cooling (or, in short, cogeneration). Cogeneration, which is a specific type of dispersed production method, involves the production of two or more forms of energy (such as electrical, thermal and cryogenic energy) from a simple primary source (such as the chemical energy of different fuels).

Since in the cogeneration model, the primary energy consumed, i.e. electricity, heat and refrigeration are supplied through a given fuel system, thus reducing the cost of energy supply substantially. In common ways, consumers have to buy their own electricity from the grid and on the other hand incur separate costs for their heating and cooling. While in the cogeneration

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mode used in the form of distributed generation, the consumer is independent of the global electricity grid and, on the other hand, because it utilizes the energy content of the incoming fuel ultimately (up to 90%), the rate and the cost of energy consumed is drastically reduced (Hou et al., 2018).

Combined cooling, heat, and power (CCHP) system consist of four main parts: primary actuator, generator, heat exchanger and control system. In the production of the compressor, a primary actuator (engine or turbine) first releases the chemical energy of the fuel and converts it into mechanical output in the output shaft. Then, the drive shaft is coupled to a generator and power is generated (Ebrahimi and Derakhshan, 2018). Sources of heat energy dissipation, including heat generated by the gases from the primary actuator, the primary actuator water cooling cycle, and the oil used to lubricate, have been identified, and by appropriate heat exchangers, heat dissipation in the form of high temperature heat (heat) Applicable Recycled. The unique properties of CCHP systems are achieved by providing the possibility of heat dissipation in the power generation process. Finally, the recycled heat is used as the energy required by absorption chillers to meet the cooling needs. Fig. 1 shows the model for residential CCHP.

From the figure, it is observed that in the electricity, heat and cold cogeneration system, fuel is used in the primary actuator to meet the building's electricity demand. The heat recovered from the primary actuator is also used to provide heat by coil heating or cooling by absorption chiller. This paper presents a multi-criterion evaluation of a 5 kW residential CCHP stack, a heat recovery system, a small absorption chiller and auxiliary component including gas compressor and humidifier with PEMFC as the primary mover from different points. The principal contributions of the proposed system are:

- (1) Proposing a new CCHP configuration based on PEMFC
- (2) Designing a new modified version for emperor penguin optimization algorithm
- (3) Analysis of the Exergy and Energy performances
- (4) Proposing a Multi-objective methodology for the case study

2. Literature review

As aforementioned, one of the best ways to optimally consume thermal energy derived from fossil fuels is to use co-generation systems of power, heat and refrigeration (CCHP). In such systems, the efficiency of the system can be increased by up to 85% by recovering the heat from the heat generated from the combustion hot water as well as the cooling water and oil in the electricity generation systems, recently, CCHP systems have been turned into a widely used power generation technology in different countries (Hua et al., 2018). The CCHP system usually includes primary actuators, heat recovery systems, heat exchangers, absorption chillers and control equipment. Important early drivers include gas and steam turbines, internal combustion engines, micro-turbines, and fuel cells. Among different movers, fuel cells due to their benefits for using as high efficiency as well as the reduction of pollutants as a renewable energy sources are become so popular (Paria et al., 2019). At present, there are several types of fuel cells such as proton exchange membrane (PEMFC) (Gholamreza and Ghadimi, 2018), phosphoric acid (PAFC) (Yang et al., 2017), solid oxide (SOFC) (Abbas Rahimi and Ghadimi, 2017), and molten carbonate (MCFC) (Farzaneh et al., 2019) which each of them has its own advantages and disadvantages. Researchers concluded that among different kinds of fuel cells, PEMFC gives the best efficiency in the residential CCHP systems (Melika et al., 2018). Some of the researches which have done in the area of residential CCHP systems are given in the following.

Zhang et al. (2012) proposed a bare-bones multi-objective particle swarm optimization algorithm for environmental/economic dispatch problems. The proposed algorithm contains three main contributions: a particle updating with no needing to tune up, a mutation operator, and a method based on particle diversity for updating. The method has been applied to the IEEE 30-bus test system and the results have been compared with seven multi-objective optimization algorithms and three well-known multi-objective particle swarm optimization techniques. The results show the superiority of the proposed method toward the others.

Chen et al. (2015) presented a new residential micro-combined CCHP along with a PEMFC stack, a single effect absorption chiller and accessories. The study showed that operating temperature is an important effective parameter on chiller and CCHP efficiency. Simulation results showed that the presented CCHP system in summer and winter gives 70.1% and 82%, respectively.

Chen et al. (2016) a new dual power source residential CCHP system based on PEMFC and PTSC. The system guaranteed a high performance for PTSC based on low temperature and high current density. The system gave high performance for the system at a relatively low solar radiation. For economic study of the system, government subsidy was also considered and the system environmental efficiency was studied based on parametric analysis.

Chang et al. (2017) analyzed a hybrid PEMFC micro-CCHP system combined with an vapor compression cycle and organic Rankine cycle. The system was analyzed both in summer and in winter. Simulation results showed an average efficiency of 75.4% in summer and 85.0% in winter for the system. The results showed that the presented method can be also reduced into a CHP or CCH system under particular conditions.

Hwa (2017) studied an exergy and energy based analysis on a high-temperature PEMFC-based 8 kW micro-CCHP system. the system analyzed for six organic working fluids. Final results showed that the average coefficient of performance (COP) of the CCHP system is 1.19 and 1.2 in summer and winter, respectively. The results also showed that both the current density and operating temperature have high impact on the energy performance of the CCHP system, while only the current density impacts on the exergy.

Romdhane and Louahlia-Gualous (2018) assessed a small scale energy efficiency of PEMFC based micro-CCHP (MCCHP) system with absorption chiller French residential application. They analyzed the MCCHP efficiency and energy saving for the different regions. Three MCCHP operational energy strategies were studied. Simulation results showed that the maximum Fuel Energy Saving Ratio is about 35% which is achieved for a single-family house located at Marseille.

Chang et al. (2019) presented a technical efficiency study of a MCCHP system based on high temperature PEMFC and solar energy. The analysis was applied based on the economic, environmental, and thermal performance analysis models. The results were applied to two case studies and the results were compared. With regard to the above studies, it is obvious that there are several researches about CCHP evaluation. Some of them worked on the optimization and multi-criteria assessment of the fuel cell based CCHP systems that can noticeably develop the CCHP system efficiency.

The main purpose of the present paper is to propose a multicriteria assessment study on 5 kW PEMFC based residential CCHP system based on a improved technique, called Improved Emperor Penguin Optimizer (EPO). Simulation results show that using the proposed optimization algorithm compared with un-optimized system gives better efficiency.



Fig. 1. The system model for residential CCHP.

3. Modeling of the combined cooling, heating, and power system

The application of CCHP systems is one of the most recognized solutions in the world in solving energy-related problems, including increasing energy demand, increasing energy costs and environmental concerns. The CCHP system is the energy supply system in which the electricity required on site is generated by a primary actuator and the heat dissipated is recovered from the primary actuator in order to provide heating and cooling. Through heat recovery, the CCHP system can achieve a total efficiency of about 60% to 90%. One of the applications of the cogeneration system is the construction part which has usually the largest share of primary energy consumption.

The main parts of a CCHP includes chillers and gas turbine where connected to the power plant to generate cooling, heating, and power energy for the customers. This is generated by gasgenerating generators and from combustion heat which has a temperature of about 753 K to heat boilers or converters and to heat up absorbent chillers. With regards to Fig. 1, the analyzed CCHP system has six principal elements: compressor to compress the air and hydrogen in to the humidifier, humidifier for humidify the input gasses for injecting it into the PEMFC, PEMFC to convert the humidified gasses energy into the electricity energy, heat exchanger unit to supply water high temperature, cooling tower to reduce the temperature of water supply for use in absorber chiller condenser, and steam adsorption chillers for adopting in cooling the houses.

The first and the second laws of thermodynamics can be used for modeling of the CCHP process (Hadi Chahkandi et al., 2019; Mehrdad Tarafdar and Ghadimi, 2015). In the present work, the second law of thermodynamics has been used by giving a precise evaluation of the exergy and the performance of the CCHP system as follows:

$$\eta_{exergy} = \frac{P_{elec} + P_{cool} + P_{hwater}}{P_{exfuel}} \tag{1}$$

where, P_{elec} is the generated electrical energy in the CCHP system and P_{cool} describes the output exergy of cooling capacity and is formulated as follows:

$$P_{cool} = Q_c \times \left(\frac{T_{amb}}{T_{cool}} - 1\right)$$
⁽²⁾

where, T_{cool} and T_{amb} represent the temperature for the cooling water of chiller and the ambient and P_{Hwater} describes the output exergy of the hot water as follows:

$$P_{\text{Hwater}} = Q_{Hwater} \times \left(1 - \frac{T_{amb}}{T_{Hwater}}\right)$$
(3)

where, T_{Hwater} represents the temperature for hot water.

 $P_{\text{exfuel},\text{CCHP}}$ is the consumed exergy fuel in CCHP system that is obtained by the following equation:

$$P_{exfuel} = S_{H2} \times CE_{H2} \times R_{H2} \tag{4}$$

where, S_{H2} represents the hydrogen stoichiometry, CE_{H2} is the chemical exergy for 1 mol hydrogen at standard condition, and R_{H2} represents the molar rate for the hydrogen (mol/s).

There are plenty of evaluation methods for economic assessment of the energy systems, such as total investment cost, payback period, present value, and internal rate of return. This study works on the annual cost to analyze the economy behavior of CCHP system within 20 years life time. This index is achieved as follows:

$$Co_{Total} = Co_{inv} + Co_{maint} + Co_{fuel}$$
(5)

where, Co_{inv} describes the initial system investment, Co_{maint} represents the maintenance cost of CCHP system (\$), and Co_{fuel} is the total fuel cost of CCHP system (\$). Table 1 illustrates the utilized economical parameters for the CCHP System components, where, fuel cost contains the produced hydrogen based on wind energy electrolysis and initial investment cost for PEMFC including auxiliary devices.

The total fuel cost for CCHP system is formulated below:

$$Co_{fuel} = T_{rp} \times Co_{H2} \times R_{H2} \times S_{H2} \times Mm_{H2}$$
(6)

Table 1	
Utilized economical parameters for the CCHP system components.	

System section	Value	Cost
Maintenance cost	Annual	6% investment
Single effect lithium bromide	532 \$/kg	5326 \$
absorption chiller		
Hot water tank	6.1 m ³	442 \$
PEMFC initial investment cost	4.9 kW	11980 \$
Fuel cost	Unit cost: 5.87 \$/kg	

Table 2

PER during hydrogen generation.

	$NO_x (g/MJ)$	GHG (g/MJ)	CO (g/MJ)
Total pollutant emissions	0.02	19.9	0.014
Hydrogen compression	0.01	14.2	0.009
Hydrogen production	0.01	6.85	0.005

where, T_{rp} represents the total running time of CCHP system (year), Co_{H2} is the unit cost of the generated hydrogen (\$/kg), and Mm_{H2} describes the molar mass of hydrogen (kg/mol).

Finally, the mean annual cost of the CCHP is formulated as below:

$$Co_{med} = \frac{Co_{total}}{T_{rp}} \tag{7}$$

4. Modeling for environmental assessment

As before mentioned there are plenty of techniques for environmental assessment of an energy system such as pollutant emission reduction and emissions of pollution gas (GHG, CO₂, SO_X, NO_X) (Bauen and Hart, 2000). A feasible way for measuring the pollution situation is to employ the pollutant penalty for translating the effect of environment in the economic cost. Unlike other popular power systems such as boiler and gas turbine, the proposed PEMFC based CCHP system is fed by auxiliary generation and hydrogen that produces water in the process of electricity production with almost no pollutant emission.

The main part of this study is to utilize a coal-based power station with the same power capacity for comparison and analyzing the pollutant emission reduction (PER) of the CCHP system. Here, after evaluating the pollutant emission during the hydrogen generation as the total PER of CCHP system, the system cooling, heating, and electric power have been obtained that are converted as equivalent electric power generated by the CCHP system.

Afterward, pollutant emissions of the coal-fired energy generation unit are evaluated equivalent to electric power and finally, the pollutant emission reduction of the CCHP system has been achieved.

The presented work considers the hydrogen generation unit separate from the main system. However, to achieve a proper system analysis about the impact of the environment in the CCHP system, the pollutant emitted during hydrogen production is considered.

Table 2 illustrates the pollutant emissions rate (PER) during the hydrogen generation process from the wind energy pollutants emitted during the water electrolysis process and power production, hydrogen compression, and their total amount.

The following equation shows how to obtain the annual GHG generated in the hydrogen production process:

$$Em_{H2} = HV_{H2} \times E_{GHG} \tag{8}$$

where, HV_{H2} represents the heat value of the annual hydrogen consumed by CCHP system (MJ) and E_{GHG} is the GHG emission in the hydrogen generation process based on wind energy (g/MJ).



Fig. 2. The architecture of CCHP optimization based on IEPO algorithm.

By considering the generated energies with the CCHP system including cooling, heating, and electric power, the equivalent electric power of all them is achieved to obtain a fair comparison with the coal-fired power station:

$$E_{eq} = E_{PEMFC} + E_{Hwater} + E_{cool} \tag{9}$$

where, E_{PEMFC} describes the electric power of PEMFC stack, and E_{Hwater} and E_{cool} represent the converted electric power from hot water and cooling capacity, respectively which are achieved by the following equations:

$$E_{hwatr} = \frac{3600 \times Q_{Hwater}}{COP_{wH}} \tag{10}$$

$$E_{cool} = \frac{3600 \times Q_{cool}}{COP_{tc}} \tag{11}$$

$$E_{PEMFC} = 3600 \times P_{el} \tag{12}$$

where, Q_{cool} and Q_{Hwater} represent COPs of conventional electric air conditioner and water heater, respectively.

To do the comparison, the pollutant emission of the coalfired plant should be also achieved. This parameter is formulated below:

$$Em_{station} = E_{eq} \times Em_{GHG} \tag{13}$$

where, Em_{GHG} describes the GHG emission produced in the power generation (g/kWh) process (Chen et al., 2016).

Finally, the annual GHG reduction is achieved by the following equation:

$$Em_{reduction} = Em_{station} \times 1 \ year - Em_{H2} \tag{14}$$

5. Optimization process

Due to the high impact of operating parameters on the system performance in different terms of economy, environment, and thermodynamics, they have very important role in the optimization process. In this study, the optimization of the parameters for the PEMFC stack has been considered to increase the performance of the CCHP system. Fig. 2 shows the PEMFC parameters which have been employed for optimization and improving the system efficiency.

The objective function contains different parameters including the energy efficiency, the exergy efficiency, the GHG reduction, and the environmental and economic evaluations. Fig. 2 shows the architecture of CCHP optimization based on IEPO algorithm.

6. Improved Emperor Penguin Optimizer (EPO)

6.1. Emperor penguin optimizer

Penguins are very intelligent and have good emotional relationships with humans, penguins are birds that cannot fly but swim very well and spend most of their lives at sea. One of the well-known of the penguins is the emperor penguin. Emperor penguin that is scientifically called Aptenodytes forsteri, is the tallest and heaviest penguin. The length of an emperor penguin is up to 5 cm in height and weighs between 1 and 2 kg. The bird's tall stature is complemented by feathers that have a dazzling black and glittering white. What adds to its beauty is a piece of golden feathers that glows on either side of the neck. The wings in this tropical bird have become swimming fins. The legs are also short and are positioned on the back of the body so that the bird can stand up and walk like a human.

The Emperor penguin's biological range is the cold water of the Antarctic and only comes out of the water for a long time to reproduce. At this time, they choose to stay on the continental shelf icebergs or in the inland islands in the southernmost region. The emperor penguin is the master of the survival. Annually lives a long time in one of the most unfavorable places (Antarctica) on earth, which is also the worst in the climate (winter season). The way of surviving the emperor penguins from this unfavorable condition is based on their huddling behavior. This behavior of emperor penguins includes four steps (Waters et al., 2012):

- Create determine the huddle border for the emperor penguins.
- (2) Evaluate the temperature profile within the huddle.
- (3) Specify the distance between emperor penguins.
- (4) Relocation of the effective mover.

A significant characteristic of the huddling behavior is the equal chance of each penguin to the warmth of huddle. Fig. 3 shows the huddling behavior of the emperor penguins. In this figure, the emperor penguin (X^*, Y^*) updates the position based on the other emperor penguins positions and obtains different number of places about the present position.

The above behavior was become an inspiration to Dhiman and Kumar (2018) to introduce a new meta-heuristic algorithm called emperor penguin optimizer (EPO). Meta-heuristic algorithms are some kinds of methods that are used for solving the optimization problems (Razmjooy et al., 2016; Namadchian et al., 2016; Bansal, 2019; Razmjooy and Ramezani, 2014). The main idea in this algorithm is to find the best effective mover. The penguins huddle is modeled as two dimensional L-shape polygon planes. At first, the huddle border is randomly generated by the emperor penguins.

Afterward, the temperature profile within the huddle is evaluated. For helping to improve the algorithm in terms of exploration and exploitation, the distance between emperor penguins is evaluated and finally, the effective mover that includes the best optimal solution is achieved and re-evaluates the huddle border with updated positions from the search agents (emperor penguins). In the following, more details of the algorithm modeling have been explained (Hao et al., 2019).

As before mentioned, during the huddling process, emperor penguins re-locate themselves on a polygon shape grid border. Each emperor penguin has at least two neighbors that are selected randomly in the huddle (see Fig. 3). However, the wind flow is faster than the movement of a emperor penguin, it should be achieved to find the huddle border around a polygon. Assume Ω is the wind velocity and Θ describes its gradient, i.e.

$$\Theta = \nabla \Omega \tag{15}$$

Vector \varnothing is combined with Ω to provide the complex potential.

$$\mathbf{F} = \boldsymbol{\Omega} + \mathbf{i}\boldsymbol{\varnothing} \tag{16}$$

where, F represents an analytical function on the polygon plane and i determines the imaginary constant. This two-dimensional behavior can be seen in Fig. 3. In Fig. 3, each emperor penguin can update its position randomly towards the position of emperor penguin that is to be positioned at the center of L-shaped polygon area with highest effective fitness rate during iteration process.

In the following, the emperor penguins huddle is modeled. The huddle process is performed by the emperor penguins to maximize the temperature in the huddle. For mathematical modeling of this process, the temperature is assumed T = 0 when the radius of polygon is greater than 1 (R > 1) and temperature is assumed T = 1 when the radius is less that 1 (R < 1).

The temperature here is the operator for exploitation and exploration of the emperor penguins with different positions. The mathematical model for temperature profile around the huddle is formulated as follows:

$$\Gamma' = T - \left(\frac{I_{\rm M}}{I_{\rm c} - I_{\rm M}}\right) \tag{17}$$

$$T = \begin{cases} 0, & \text{if } R > 1\\ 1, & \text{if } R < 1 \end{cases}$$
(18)

where, *R* represents the radius, T is the time to find the best solution, and I_M and I_c are the maximum iteration and the current iteration, respectively.

The next parameter for modeling is to find the distance between the emperor penguins and the best obtained position after the huddle border generating. This process can be modeled by the following equation.

$$\vec{D}_{ep} = \left| S\left(\vec{A}\right) \times \vec{P}\left(\mathbf{I}_{c}\right) - \vec{C} \times \vec{P}_{ep}\left(\mathbf{I}_{c}\right) \right|$$
(19)

where, *S* (.) describes the social forces of the emperor penguins to force them to move into the direction of the best solution, \vec{P} is the best optimal solution, and \vec{P}_{ep} indicates the position vector of the emperor penguin. \vec{A} and \vec{C} are employed to prevent of collusions between neighbors and are achieved by the following formulas:

$$\vec{A} = (M \times P_{grid}(accuracy) \times Rand()) - T'$$
(20)

$$\vec{C} = \text{Rand}() \tag{21}$$

and, where, *M* determines the movement parameter which keeps a gap between emperor penguins (here, M = 2), $P_{grid}(a)$ is the polygon grid accuracy by the comparison between emperor penguins, *T'* describes the temperature profile inside the huddle, and *Rand*() represents a random function lies in the interval 0 and 1.

The function *S*(.) is formulated as follows:

$$S\left(\vec{A}\right) = \left(\sqrt{c_g \times e^{-l_c/c_l} - e^{-c_g}}\right)^2 \tag{22}$$

where, *e* defines the exponential function, c_g and c_l describe the control parameters for better exploration and exploitation such that $c_g \in [2, 3]$ and $c_l \in [1.5, 2]$, respectively. The next process which should be modeled is the relocation of the mover. Based on this mechanism, each emperor penguin is updated based on the best achieved optimal solution.

This mechanism is responsible to change the positions of other search agents in the search space. To update the position of an emperor penguin based on this mechanism, the following equation is employed.

$$\vec{P}_{ep}\left(\mathbf{I}_{c}+1\right) = \vec{P}\left(\mathbf{I}_{c}\right) - \vec{A} \times \vec{D}_{ep}$$
(23)

where, P_{ep} (I_c + 1) is the next updated position of emperor penguin.

This process repeats if the huddling behavior of the emperor penguins is reevaluated after the mover re-location.

6.2. Improved Emperor Penguin Optimizer(IEPO)

From the EPO equations, the parameter \vec{C} is a random value. Singer mechanism is used as a chaos mechanism to improve the



Fig. 3. The huddling behavior of the emperor penguins.

 Table 3

 The standard benchmarks employed for algorithm validation

Benchmark	Formula	Constraints	Dimension
Demeninark	Iomula	constraints	Dimension
Rastrigin	$F_{1}(x) = 10D + \sum_{i=1}^{D} (x_{i}^{2} - 10\cos(2\pi x_{i}))$	[-512, 512]	30-50
Rosenbrock	$F_{2}(x) = \sum_{i=1}^{D-1} \left(100 \left(x_{i}^{2} - x_{i+1} \right) + (x_{i} - 1)^{2} \right)$	[-2.045, 2.045]	30–50
Ackley	$F_{3}(x) = -20 \exp\left(-0.2 \sqrt{\frac{1}{D} \sum_{i=1}^{D} (x_{i}^{2})}\right) - \exp\left(\frac{1}{D} \sum_{i=1}^{D} (\cos(2\pi x_{i}))\right) + 20 + e$	[-10, 10]	30-50
Sphere	$F_4(x) = \sum_{i=1}^{D} x_i^2$	[-512, 512]	30-50

system convergence speed (Yang et al., 2007; Rim et al., 2018). To implement this mechanism, the unknown scale factor (\vec{C}) is converted into regular formulated value as follows:

$$\vec{C}_{i+1} = 1.07 \left(7.9 \vec{C}_i - 23.3 \vec{C}_i^2 + 28.7 \vec{C}_i^3 - 13.3 \vec{C}_i^4 \right)$$
(24)

In addition, there is premature convergence in EPO. To cover this shortcoming, Lévy flight (LF) has been employed. LV is a strong mechanism that is widely used in bio-inspired optimization algorithms for improving their premature convergence (Choi and Lee, 1998). This mechanism uses a random walk approach to proper control of the local search that is mathematically formulated as follows:

 $Le\left(w\right)\approx w^{-1-\tau}\tag{25}$

$$w = \frac{A}{|B|^{1/\tau}} \tag{26}$$

$$\sigma^{2} = \left\{ \frac{\Gamma(1+\tau)}{\tau \Gamma((1+\tau)/2)} \frac{\sin(\pi \tau/2)}{2^{(1+\tau)/2}} \right\}^{\frac{2}{\tau}}$$
(27)

where, τ describes the *LV* index in the interval [0, 2] (here, $\tau = 3/2$ Li et al., 2018), $A \sim N(0, \sigma^2)$ and $B \sim N(0, \sigma^2)$, Γ (.) determines Gamma function, *w* is the step size, A/B ~ N(0, σ 2) means that the samples generate from a Gaussian distribution in which mean is zero and variance is σ^2 , respectively.

By considering the above cases, the update formulation for two updating models is as follows:

$$\vec{P}_{ep}\left(\mathbf{I}_{c}+1\right) = \left(\vec{P}\left(\mathbf{I}_{c}\right) - \vec{A} \times \overrightarrow{D}_{ep} \times \operatorname{Le}(\delta)\right)$$
(28)

The flowchart of the presented IEPO is shown in Fig. 4.

Table	4
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The obtained results of the different algorithms	for	validation.	
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Ma	rk	IEPO	GA Holland (1992)	SSO Bansal (2019)	WCO Razmjooy et al. (2016)	EPO
f1	MD	0.00	70.61	74.24	2.19	2.28
	SD	0.00	1.66	8.96	4.35	3.53
f2	MD	6.19	35.41	200.1	13.16	13.10
	SD	2.24	27.15	59.00	4.62	4.72
f3	MD	0.00	3.19e-2	8.26	3.14e-3	6.32e-16
	SD	0.00	2.14e-2	1.19	1.12e-3	0.00
f4	MD	0.00	1.15e-4	8.27e-4	6.19e-9	0.00
	SD	0.00	3.14e-5	5.12e-4	3.28e-9	0.00

6.3. The validation of the algorithm

For the performance analysis of the proposed method and validating it's efficiency, it is compared with some different algorithms including genetic algorithm (GA) (Holland, 1992), shark smell optimization (SSO) algorithm (Abedinia et al., 2018), world cup optimization algorithm (WCO) (Razmjooy et al., 2016), and the original EPO (Dhiman and Kumar, 2018). Four standard benchmarks have been used for the algorithm analysis. Table 3 illustrates these benchmarks.

Table 4 declares the simulation results of different algorithms on the studied benchmarks by considering 30-dimensions. As it is observed, the optimal value for the proposed method by considering the mean deviation (MD) and the standard deviation (SD) overcomes all the algorithms.

The results illustrated that the proposed method has better results than the other methods.



Fig. 4. The flowchart diagram of the proposed IEPO algorithm.

7. Optimization of the CCHP system based on IEPO algorithm

The optimization process in this study is based on the PEMFC parameters including exergy, system efficiency, annual cost, and GHG reduction. Fig. 5 shows the brief results of these indexes based on the proposed system. As can be seen from the figure, a linear increasing is happened for the annual cost of the studied CCHP system because fixing the initial investment cost makes the hydrogen cost as the principal supply of the system cost, while, here, current density of PEMFC is the only effective parameter on the hydrogen consuming ratio with linear relation between the current density and the annual cost.

Due to the current density increasing, system has low variations in terms of performance. The exergy performance has been reduced from 39.4% to 33.6% due to the concentration voltage loss which shows that chiller translates more chemical energy into the waste heat. During the current density increasing, the annual GHG has been increased and reaches to a maximum value of 1.62×10^7 g at 886 mA/cm² and then it has been decreased due to the system equivalent power fluctuation. High current density increases the annual cost and annual GHG reduction and decreases exergy performance.

Table 5 illustrates the optimum values of the annual cost, annual GHG reduction, and exergy efficiency for the proposed method based on IEPO and its comparison with standard EPO and also NSGA-II as a popular optimization algorithm.

As it is observed, the maximum values of annual GHG reduction and exergy efficiency are 5.61e6 g and 51.3%, respectively, while, annual cost can be decreased to 3.24e3 **\$**.

8. Simulation results

In this section, the results of the optimized CCHP system based on the improved emperor penguin optimization algorithm



Fig. 5. The result of indexes changing in the studied CCHP system.



Fig. 6. The simulation results of the annual GHG reduction per year before and after optimization by the IEPO algorithm.

Table 5

The results of optimized CCHP system.

Algorithm	Value	Exergy efficiency	Annual Cost	Annual GHG reduction
IEPO	Minimum	38.4%	3.24e3 \$	5.61e6 g
	Mean	47.6%	11.27e3 \$	2.83e7 g
	Maximum	51.3%	26.49e3 \$	3.14e7 g
EPO	Minimum	35.2%	3.945e3 \$	4.25e6 g
	Mean	43.1%	13.28e3 \$	2.16e7 g
	Maximum	49.4%	28.17e3 \$	2.63e7 g
NSGA-II Chen et al. (2018)	Minimum	32.3%	4.627e3 \$	3.7e6 g
	Mean	41.2%	14.38e3 \$	1.01e7 g
	Maximum	45.0%	29.34e3 \$	1.82e7 g

Table 6

The results of the CCHP system before and after applying the improved butterfly optimization algorithm.

Method	Operating variables				
	T (K)	RH (%)	$P_{H2} (atm)$	P _{air} (atm)	J (mA/cm ²)
Before optimization	368	100	2	2	800
After optimization	342	100	3.3	1.8	984

have been given. Table 6 declares the operation values obtained by the CCHP system before and after optimization process by considering extreme values for annual cost, exergy efficiency, and annual GHG reduction.

Fig. 6 shows the simulation results of the annual GHG reduction per year before and after optimization by the IEPO algorithm. The simulation is performed during the startup running period. Figure shows an explicit increasing in the GHG reduction. This declares that high current density increases the difference of the annual GHG reductions of the system.



Fig. 7. The simulation results of energy efficiency before and after applying IEPO algorithm.



Fig. 8. The simulation results of exergy efficiency before and after applying IEPO algorithm.

In addition, the annual GHG reduction at final optimal point is 1.49e7 g. This gives two important affects. The first is that increasing the current density decreases the GHG emission. The second is that adopting the IEPO algorithm in CCHP system gives better environmental performance.

Fig. 7 shows the results of the energy efficiency for the presented CCHP system before and after applying the IEPO algorithm. It is obvious that during the startup running process, the energy efficiency for the presented optimized system is higher than the system before optimization.

Fig. 8 shows the simulation results of exergy efficiency before and after applying IEPO algorithm. Simulation results show that the exergy efficiency at final optimal point is 42.5% which is significantly higher than the normal mode before applying the IEPO algorithm.

The results of the Figure show that during the total startup running process, the exergy efficiency for the IEPO-based system is higher than the normal system before optimization.

9. Conclusions

In this study, the performance of five kilowatts PEMFC based CCHP system based on an improved version of emperor penguin optimization algorithm is proposed. The CCHP system includes a heat recovery system, a small absorption chiller, a 5 kW PEMFC stack, a gas compressor, and a humidifier. Environment, economics, and thermodynamic indexing evaluation such as exergy efficiency, energy efficiency, annual GHG reduction, and annual cost have been used for the CCHP system performance analysis. The proposed improved algorithm is first compared with some different optimization algorithms and the results show a well improvement of the standard algorithm in terms of convergence and speed. The algorithm is then applied to the CCHP configuration and the results are compared with standard emperor penguin optimization algorithm and NSGAII as a widely used optimization algorithm. Simulation results showed that using improved emperor penguin optimization algorithm gives and high annual GHG reduction, high annual cost, and low exergy efficiency toward the compared methods.

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.

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