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Optimal Operation and Output Oscillations Reduction of PEMFC by using an Intelligent Strategy

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This paper presents a novel maximum power point control of stand-alone proton exchange membrane fuel cell (PEMFC) system using a novel optimization strategy based on the eagle strategy (ES) coupled with cuckoo optimization algorithm (COA) and particle swarm optimization (PSO) in order to track the maximum power point of PEMFC. The proposed method presents a new combination of optimization algorithms. According to this strategy, the advantages of optimization algorithms beside each other lead to reach better results in term of the convergence speed and the accuracy of the optimum operation of the system. Furthermore, the standard deviation of data produced by the proposed method is very lower than other conventional optimization algorithms; PSO and COA algorithms, so it leads to decrease the output power oscillation. To validate these advantages, the proposed tracker applied to the PEMFC system in MATLAB/SIMULINK environment. The simulation results confirm the effectiveness and accuracy of the proposed approach.

Keywords: Maximum power point tracking, Intelligent optimization algorithm, PEMFC, Particle swarm optimization, Cuckoo optimization algorithm

1. INTRODUCTION

Energy microsources such as fuel cells, photovoltaic, and microturbines are used for power distributed generation (DG) systems due to high efficiency, reliability, and some economic advantages [1]. Among these energy micro sources, the operation of fuel cells (FCs) have been developed in the last decade due to advantages and abilities of the proton exchange membrane fuel cell (PEMFC). The features of the PEMFC such as low operating temperature, quick start up, and high power density become them as a most promising technology among different green power technologies (e.g. wind power, photovoltaic, and microturbine) [2-4].

Generally, FC-DG systems are placed in power system to reinforce the grid, so it is necessary to design controllers for them in order to improve their operation characteristic and to increase reliability and efficiency of them [1, 5].

Employing the optimal control theory and its applications such as maximum power point tracking (MPPT) is very difficult and is one of the important challenges for renewable power system designers in the next decades when energy saving and finding eco-energy resources are global priorities. Therefore, the researchers are pursuing the new methods like optimization algorithms to tackle this problem. In [1, 6-7], new structures of fuzzy controller are introduced which control active power and reactive power simultaneously. In [8-10], the extremum seeking control is used to track the maximum power point, which they use a periodic signal to find an operation point near the optimum one. The simulation results of MPPT by PI controller, conventional fuzzy logic controller, and adaptive fuzzy logic controller are compared in [11] and it is shown that the adaptive fuzzy logic controller has better performance and more efficiency. Since the response of FC system depends on the flow and pressure regulation of the air and hydrogen, and also water management, authors in [12] compute the optimal value for oxygen stoichiometry reference in order to maximize the FC output power at each computing time. In [13, 14], the P&O algorithm is used in a fuel cell/battery hybrid system to optimize the operation of the system by maximizing the output power of the FC, as well. Sliding control in fuel cell hybrid systems is applied to control the hydrogen and oxidant supply on PEMFC stacks in [15, 16]. Fuzzy- sliding mode is another MPPT approaches presented in [17].

This paper presents a new two-stage strategy to achieve the minimum output oscillations and optimal operation of the PEMFC system. This strategy uses different optimization algorithms in each stage under different conditions. The accuracy and tracking speed of conventional optimization algorithms are improved by combination with each other, and this strategy benefits from this idea. In the first stage, the particle swarm optimization (PSO) [18, 19] algorithm explores the search space crudely and the best solution of the first stage is fed to the second stage. In the second stage, the cuckoo optimization algorithm (COA) [20] is employed in the search space in order to detect the global best solution around the best solution of the first stage. This process is repeated till the best solution meets the defined criteria as an error signal and so the operation of the system will become optimum. So the higher performance in terms of accuracy and speed are two main advantages of the proposed approach.

The rest sections of this paper are organized as following: section 2 describes the details of fuel cell model and its operation. The structure of PSO and COA algorithms and also the proposed strategy called eagle strategy and simulation results are given in section 3. In section 4 conclusions are presented.

2. FUEL CELL BASIC OPERATION AND MODEL

Fuel cell is a device that converts chemical energy from the fuel (the fuel is commonly hydrogen, but sometimes the hydrocarbons as natural gas is used) into the electrical energy. The structure of a cell consists of two electrode known anode and cathode which separated by an electrolyte (Fig.1). The electrical current is produced as follow:

- The hydrogen is fed into anode (negative electrode), and the electrochemical oxidation occurs.
- Oxidant is fed into cathode (positive electrode) and reduces the electrochemical oxidation, so the electrical current is produced.

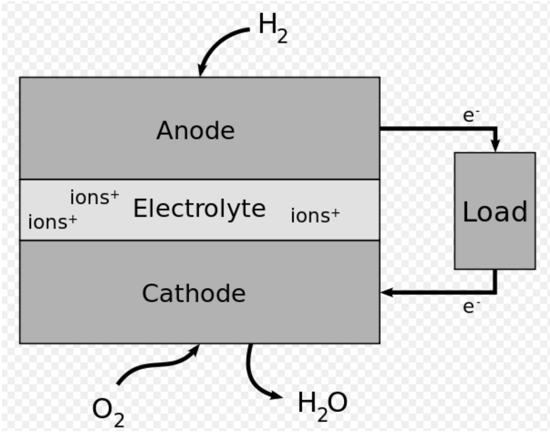


Figure 1. Schematic diagram of fuel cell basic operation.

The optimal operation of the FC is divided into two parts, the electrical and thermodynamic parts, which the thermodynamic efficiency depends on the fuel process, water management and temperature control of the system and the electrical efficiency depends on the activation and concentration losses apart from ohmic loss [3].

Generally, the voltage losses of PEMFC consist of three main terms: activation loss, Ohmic loss, and concentration loss, which the FC output voltage is obtained by subtracting them from open-circuit thermodynamic potential [15]:

$$V_{\text{cell}} = E_{\text{Nernst}} - (V_{\text{act}} + V_{\text{ohm}} + V_{\text{conc}}) \tag{1}$$

where, E_{Nernst} is the open-circuit thermodynamic potential, and V_{act}, V_{ohm}, and V_{conc} are activation, ohmic, and concentration losses, respectively. The value of E_{Nernst} is obtained from Nernst equation as follows:

$$E_{\text{Nernst}} = 1.229 - 8.5\times10^{-4}(T - 298.15) + 4.308\times10^{-5} T\,(\ln(P_{H_2}) + 0.5\ln(P_{O_2})) \tag{2}$$

where T is the absolute temperature (in $°K$), P_{H_2} is the hydrogen partial pressure (in *atm*), and P_{O_2} is the oxygen partial pressure (in *atm*). The activation voltage loss can be given as:

$$V_{\text{act}} = e_1 + e_2 T + e_3 T\,\ln(C_{O_2}) + e_4 T\,\ln(I_{FC}) \tag{3}$$

where, parameters e_i, i=1,…,4 are parametric coefficients, I_{FC} is the FC current (in *A*), and C_{O_2} represents the dissolved oxygen concentration in the interface of the cathode catalyst that can be achieved as:

$$C_{\text{O}_2} = \frac{P_{\text{O}_2}}{5.08\times10^{6} \times \exp(-498/T)} \tag{4}$$

The ohmic voltage loss can be calculated as:

$$\begin{cases} V_{\text{ohm}} = I_{FC} R_M \\ R_M = \dfrac{t_m \times r_m}{A} \end{cases} \quad (5)$$

where, R_M is the ohmic resistance (consists of Echivalent membrane resistance and contact resistance between membrane and electrode in Ω), t_m is the membrane thickness (in *cm*), A is the activation aria (in cm^2), and r_m is the membrane resistivity (in Ωcm) which can be computed as:

$$r_m = \frac{181.6 \times [1 + 0.03(I_{FC}/A) + 0.0062(T/303)^2 (I_{FC}/A)^{2.5}]}{[\lambda_m - 0.634 - 3(I_{FC}/A)]\exp(4.18(T - 303/T))} \quad (6)$$

where, λ_m as an input of PEMFC model represents the water content of the membrane, and can vary from 0 to 14 in normal conditions and under supersaturated, it can be set to 23 maximum.

The concentration voltage loss denotes the maximum rate at which a reactant can be supplied to an electrode and is written as:

$$V_{\text{conc}} = -\frac{RT}{nF} \ln\left(1 - \frac{I_{FC}}{i_L A}\right) \quad (7)$$

where, i_L is the limiting current (in *A*). In order to increase the FC output voltage, a number of cells N_{FC} are series per string [15], so the FC output voltage can be calculated as:

$$V_{FC} = N_{FC} \times V_{cell} \quad (8)$$

Fig. 2 represents the P-I characteristics of FC in different temperatures and Fig.3 shows the P-I characteristics of FC in different λ_m. According to this figure, there is a single maximum point in specific temperature and λ_m. In this condition, the FC system operates in the highest efficiency.

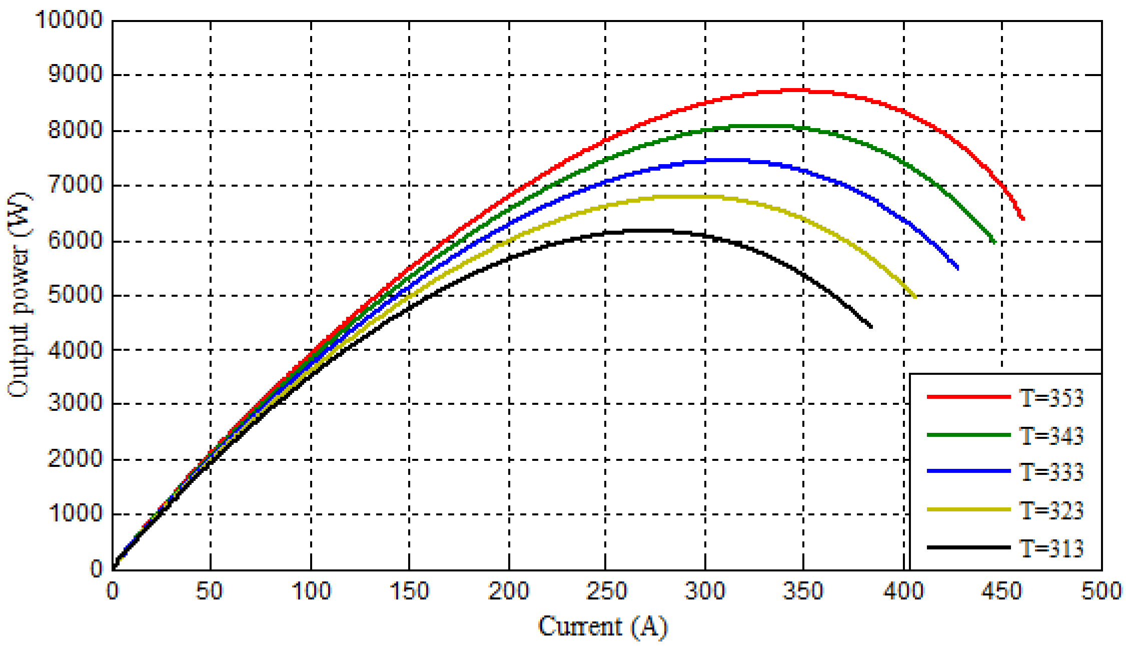


Figure 2. Output power versus PEMFC current in λ_m =13 and different temperatures.

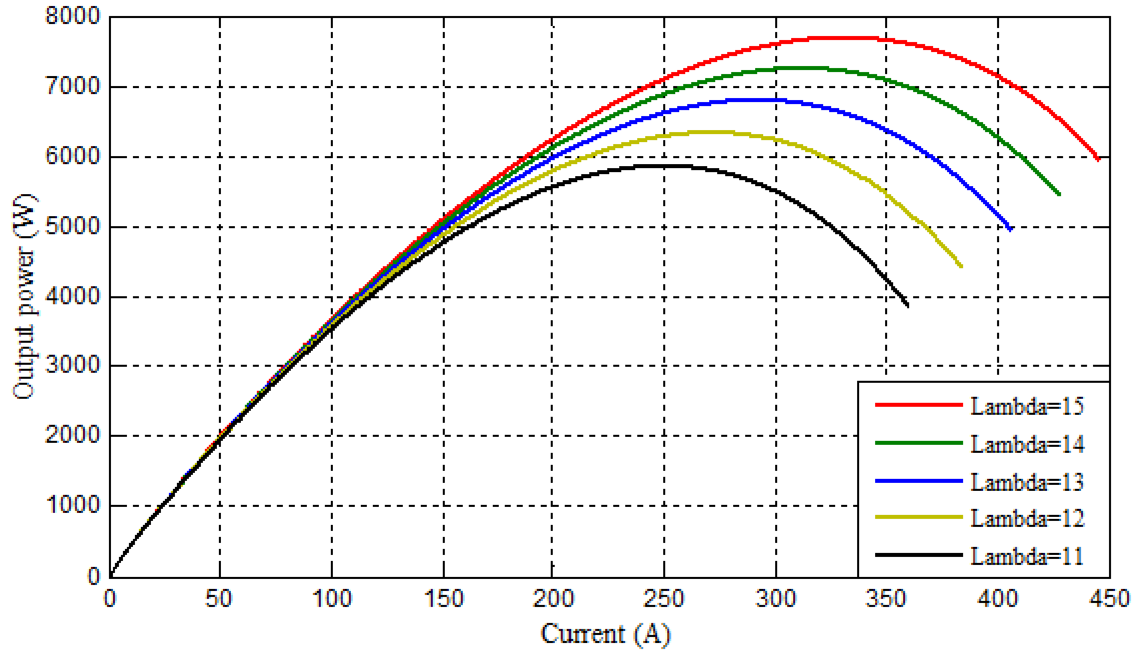


Figure 3. Output power versus PEMFC current in T=323 and different λ_m.

3. THE PROPOSED INTELLIGENT OPTIMIZATION ALGORITHM BASED MPPT

3.1. Particle swarm optimization

Swarm behavior can be modeled with a few simple models. The particle swarm optimization (PSO) algorithm originally proposed by Kennedy and Eberhart (1995) is an intelligent optimization algorithm based on the social behavior of birds, bees or a school of fishes [18, 19]. The basic concept of PSO is inspired by a large number of birds called individuals which are randomly looking for food. In this algorithm, the position of each swarm is shown by vector x and its velocity, and then each swarm tries to modify its own position and also its velocity. As each swarm knows the best global value experienced by the groups and also the best local value in each group during the search process, so the swarms move toward the bets area, i.e., the area with the best global value till the best point is found. In summary, the general steps of PSO can be described as follows:

Step 1: initialization and generation of population and initial condition of each swarm

Step 2: calculation of the objective function value for each swarm. The best objective function value experienced by each swarm is called best personal (pbest) point value and the best objective function value among all groups is called best group (gbest) value, and the swarms number is stored according to the gbest.

Step 3: modification of the search point for each swarm using Eqs. 9 to 11:

$$v_i^{k+1} = wv_i^k + c_1 r_1 \times (pbest_i - s_i^k) + c_2 r_2 \times (gbest - s_i^k) \tag{9}$$

$$w = w_{\max} - \frac{w_{\max} - w_{\min}}{iter_{\max}} \times iter \tag{10}$$

$$s_i^{k+1} = s_i^k + v_i^{k+1} \tag{11}$$

where k is the iteration number, w represents the weighting function, r is the random number between 0 and 1, c_1 and c_2 are the weighting coefficients, v_i^k is the velocity of i^{th} swarm at iteration k, s_i^k is the current position of i^{th} swarm at iteration k, $w_{\min}$ and $w_{\max}$ represent the initial and final weight, respectively, and $iter$ and $iter_{\max}$ are the current and maximum iteration number, respectively.

According to Eqs. 9 to 11, the modification of the search point for each swarm can be represented by the concept of velocity, namely modified value for the current position [18, 19]. In fact, at first, each swarm tracks the best position (with the best value) in neighboring individuals in local state, and then in the global state, the best position among them is selected.

Step 4: checking the stop criterion. If the predetermined maximum iteration number is met, the searching process will be finished, otherwise, it goes to step 2.

The flowchart of this algorithm is shown in Fig. 4.

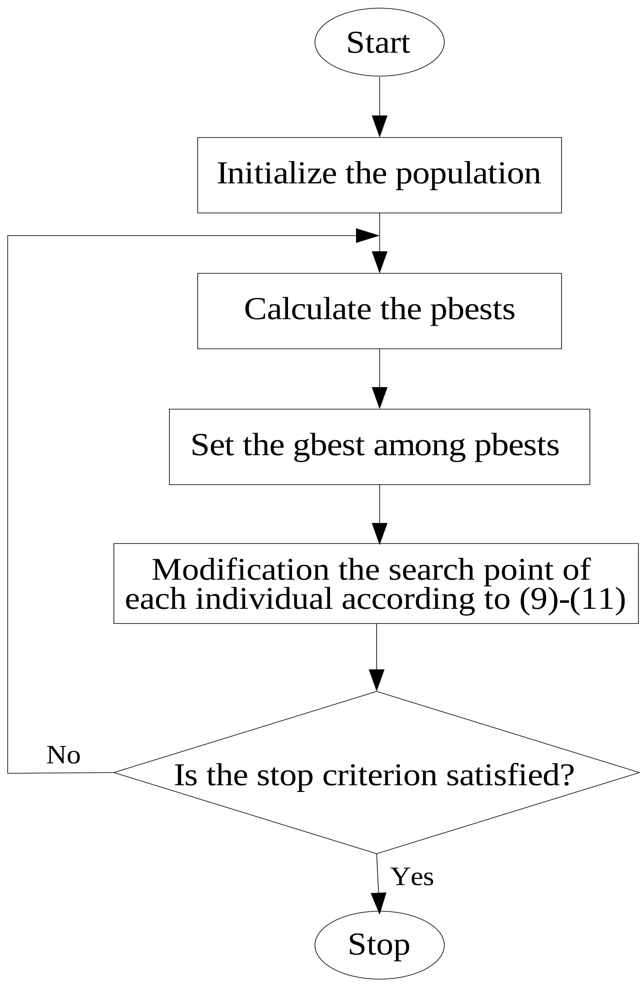


Figure 4. The flowchart of PSO algorithm.

3.2. Cuckoo Optimization Algorithm

Cuckoo optimization algorithm (COA) is an evolutionary algorithm inspired by the special behavior of the bird called cuckoo. Like other evolutionary optimization algorithms, this algorithm consists of an initial population. This population generates eggs and lays some of them in the birds' nests called host birds. The eggs laid in the host birds' nests don't have the same chance to survive, i.e., the eggs with more similarity to the host birds' eggs have more chance to survive than other eggs and the eggs that aren't similar to the host birds' eggs are detected and killed by host birds. The number of remained eggs in a region will grow up in the host birds' nests. After growing up the cuckoos' chicks, they become mature cuckoos and form different societies. Each society will have its habitat. Cuckoos in the societies select the society with the best habitat as a destination and then immigrate toward it. So, the cuckoos try to randomly lay their eggs in the nests placed inside the best habitat. This process is iterated until the best position, namely the position with the highest profit is detected by cuckoos. The general operation of COA can be summarized as follows [20]:

Step 1: Generation of the initial population called "habitat". In a N_{var}-dimensional optimization problem, this initial population is a $1\times N_{\mathrm{var}}$ array given by:

$$\text{Habitat} = (x_1, x_2, ..., x_{N_{\mathrm{var}}}) \tag{12}$$

Where, $(x_1, x_2, ..., x_{N_{\mathrm{var}}})$ are the variable values. The profit of the habitat is obtained by calculation the profit function f_p as follow:

$$\text{Profit} = f_p\,(\text{habitat}) = f_p\,(x_1, x_2, ..., x_{N_{\mathrm{var}}}) \tag{13}$$

Step 2: Generation of a candidate matrix of size $N_{pop} \times N_{\mathrm{var}}$, and Generation of the number of eggs randomly for each cuckoo habitats. Each cuckoo can lay between 5 to 20 eggs.

Step 3: Detection of the maximum distance that cuckoo can lay its eggs called "Egg Laying Radius (ELR)" according to the following equation:

$$ELR = a \times \frac{\text{Number of current cuckoo's eggs}}{\text{Total number of eggs}} \times (\mathrm{var}_{hi} - \mathrm{var}_{low}) \tag{14}$$

where a is an integer number, and handles the maximum value of *ELR*.

Step 4: Laying the eggs inside the *ELR* by cuckoos.

Step 5: Recognition of the eggs that are not similar to the host birds' eggs and killing them.

Step 6: Hatching on the remained eggs. These chicks grow up and form the different groups in the different regions.

Step 7: Selection of the society with the best profit function value as a goal point and immigration of the other cuckoos toward this point.

Step 8: Checking the stop criterion. If the stop criterion is met, the searching process will be finished, otherwise, it goes to step 2.

The flowchart of this algorithm is shown in Fig. 2 as well.

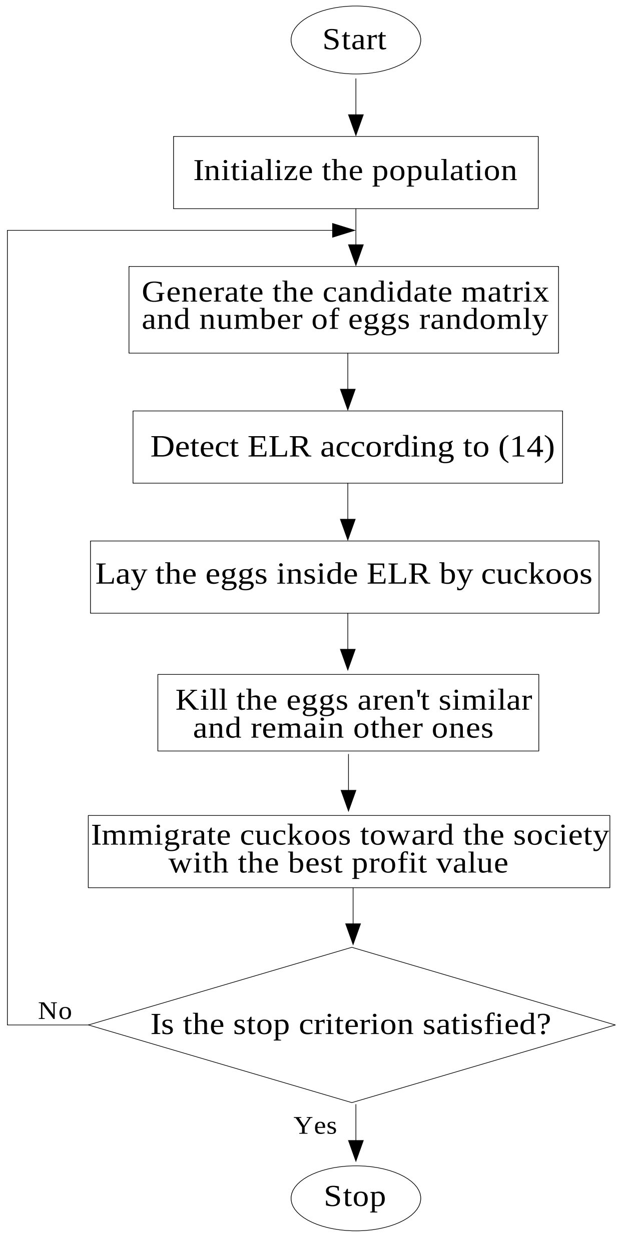


Figure 5. The flowchart of the COA algorithm.

3.3. Eagle Strategy

Eagle strategy (ES) is a two-stage optimization strategy that is proper for different purposes with a balance combination among optimization algorithms. This combination includes a crude global search and an intensive local search in which the search space is explored using crude global search, and then the intensive local search is employed in the set of promising solutions found by crude global search in the first stage. In fact, the operation of ES can be summarized in two stages:

Stage 1: Running the crude global search in the search space, and then recording the solution with the best values of the objective function

Stage 2: Employing the intensive local search around the best solutions recorded in the stage 1.

The advantage of this two-stage method and such combination is to use different algorithms in different search stages, and benefit from the advantages of different algorithms. So, it leads to reach the better results. It is vital to note that the intensive local search algorithm should be able to explore the search space diversity until no better solutions can be found. So, this strategy leads to more effective search process [21]. The flowchart of the proposed method is presented in Fig. 6.

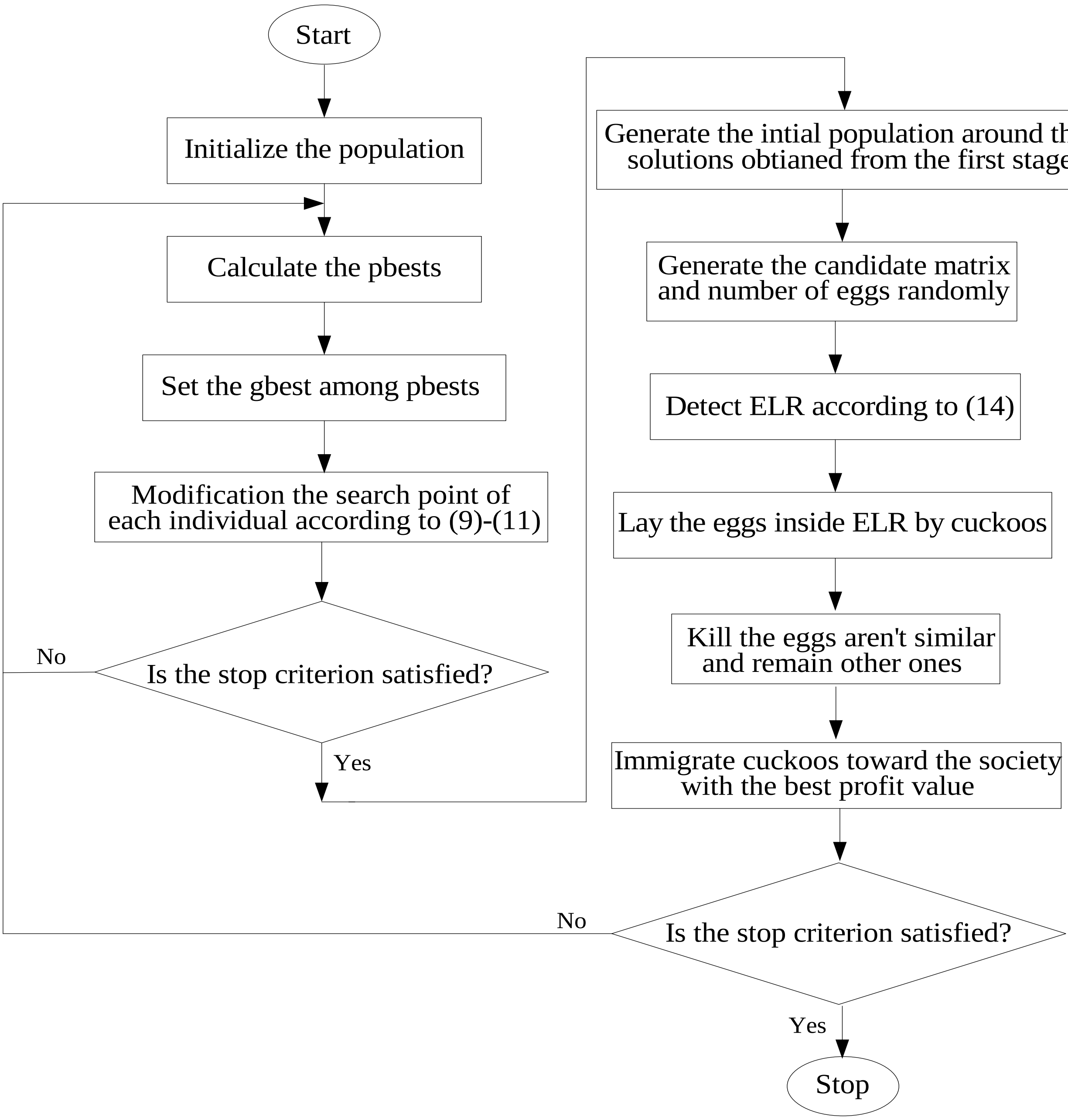
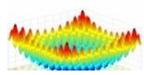
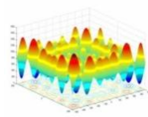
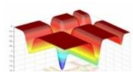
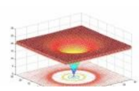


Figure 6. The flowchart of the proposed ES coupled with the PSO and COA.

3.4. Validation of the proposed ES coupled with PSO and COA using five important benchmarks

At first, in order to test and ensure the performance of the proposed optimization algorithm in different conditions, it is applied to four important benchmark functions listed in Table 1. These functions are usually used for validation of optimization algorithms. The output results of the proposed optimization algorithm have been compared with the conventional optimization algorithms such as PSO [19], COA [20]. Table 2 shows the parameter values of the optimization algorithms applied to the above benchmark functions.

Table 1. Four important benchmark functions.

Function name	Function equation	Domain	F_{min}	3D plot
Rastrigin	$f_1(x)=\sum_{i=1}^{D}(x_i^2-10\cos(2\pi x_i)+10)$ $X=[x_1,x_2,...,x_D]$	$-5.12<x_i<5.12$	0	
Schwefel	$f_2(x)=418.98287074\times D-\sum_{i=1}^{D}(x_i \sin\sqrt{\lvert x_i \rvert})$ $X=[x_1,x_2,...,x_D]$	$-500<x_i<500$	0	
Michalewices	$f_3(x)=-\sum_{i=1}^{D}(\sin(x_i)\times(\sin(\frac{ix_i^2}{\pi}))^{20})$ $X=[x_1,x_2,...,x_D]$	$0<x_i<\pi$	**	
Ackley	$f_4(x)=-20\exp(-0.2\sqrt{D^{-1}\sum_{i=1}^{D}(x_i)^2})-$ $\exp(D^{-1}\sum_{i=1}^{D}\cos(2\pi x_i)+20+\exp)$ $X=[x_1,x_2,...,x_D]$	$-32<x_i<32$	0	

** There are different optimal points in different dimensions

Table 2. Parameter values of the optimization algorithms.

Parameter values of COA	
Cuckoo population	10
a	30
Parameter values of PSO	
Particle number	10
ω	0.95
C_1	2
C_2	2
μ	1

In this case, ES coupled with COA and PSO applied to the above benchmark functions where PSO is used in the first stage, namely crude global search, and COA is used in the second stage, namely intensive local search. Table 3 shows the output results of the proposed approach, PSO, and COA when they are applied to the above benchmark functions.

In Table 3, ET is execution time, D is the dimension of the objective function, Mean is the mean value of the objective functions when the objective functions are evaluated for 10 times by the optimization algorithms, and SD is the standard deviation.

Table 3. Numerical results of the proposed approach, COA, and PSO.

f_i	D	ET (s)	Proposed approach		COA		PSO	
			Mean	SD	Mean	SD	Mean	SD
f_1	5	2	3.9435×10^{-14}	2.1478×10^{-14}	6.9988×10^{-14}	4.1156×10^{-14}	3.6584×10^{-7}	2.2895×10^{-7}
	10	3	1.0733×10^{-12}	8.6373×10^{-13}	1.0825×10^{-12}	3.0724×10^{-13}	0.5822	0.8265
f_2	5	2	0	0	0	0	9.9621×10^{-7}	4.4862×10^{-10}
	10	3	7.1057×10^{-7}	7.6126×10^{-7}	1.9931×10^{-6}	5.4038×10^{-7}	1.9839×10^{-6}	8.0217×10^{-9}
f_3	5	2	–4.9329	0.0224	–4.6877	2.9458×10^{-15}	–4.6877	4.3083×10^{-8}
	10	3	–9.6602	2.5039×10^{-8}	–9.6602	4.1470×10^{-8}	–9.6401	0.0230
f_4	5	2	0.0556	0.0342	5.4438	9.6933	2.5717	5.0945
	10	3	1.6828	3.1816	7.5524	9.3968	5.4005	4.9881

Considering Table 3, it can be seen that COA outperforms PSO algorithm (this fact has been proved in [20] previously). According to the numerical results of this table, combination of these algorithms in ES framework leads to reach better results on cases in which they are used separately. These facts are clearly observable in SD and mean values in Table3.

Since the use of FC system as a back up energy supply should be taken into consideration in hybrid power systems, extraction the maximum output power from these alternative sources by intelligent algorithms and comparison different approaches in order to choose the most efficient method is very important. However, in this paper, we are going to compare and explore four MPPT approaches that are the proposed approach, PSO, COA, and P&O when they are applied to the same FC system. The P&O algorithm based on perturb reaches the attention of researchers because of its simple structure in MPPT context in recent years [13, 14]. However, creating the fluctuation in output power because of applying perturb is the biggest disadvantage of this algorithm. The PSO algorithm is another intelligent approach that its proper performance leads to use it in the MPPT context, especially in the photovoltaic systems [22]. And finally, COA is a new intelligent optimization algorithm that is applied to the FC system for first time.

In this section, the studied FC system will be tested in different conditions divided into two case studies. In case 1, the simulation results of the proposed tracker are provided in constant temperature and membrane water content. In case 2, in order to validate the performance of the proposed tracker, some conventional MPP trackers; PSO, COA, and P&O based MPP trackers have been applied to the same FC system. All simulations have been carried out by MATLAB/SIMULINK environment, and adjusting the duty cycle of DC/DC boost converter is used to track the maximum power point of FC system. Since we are going to reduce the oscillation of the FC system output power, therefore the algorithms used for tracking purposes should have the fast operation. This purpose, namely reducing the output oscillation is obtained by reducing the execution time of the optimization algorithms, so that the time limitation is considered as a stop criterion in all algorithms. Fig. 7 shows the overall configuration of the studied FC system.

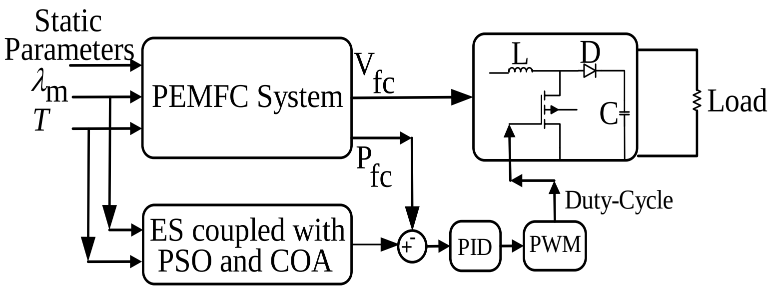


Figure 7. The general configuration of the studied PEMFC system.

3.5. Case one: normal operating condition

In this case, the operation of the system is analyzed in normal conditions, so membrane water content (λ_m) and temperature (*T*) are considered constant, and the optimum power is obtained under this situation. The simulation results in this case are presented in Figs.8-10. Figs. 8 and 9 show the P_I and V_I curves, respectively, and Fig. 10 shows the output power of the system versus time in *T*=313 and λ_m =11.

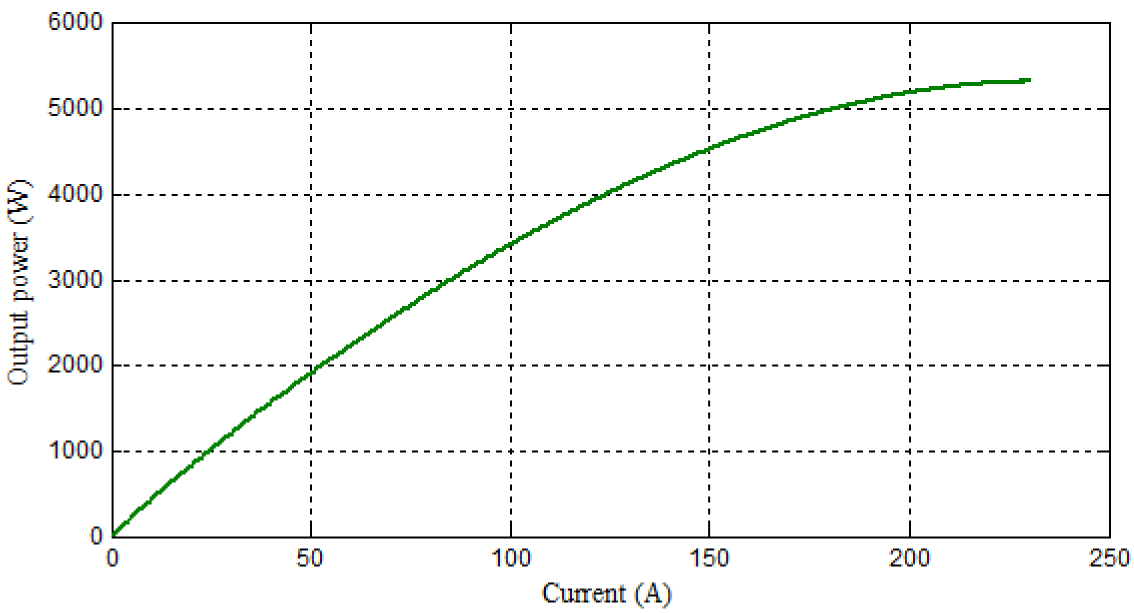


Figure 8. Output power versus PEMFC current in *T*=313 and λ_m =11.

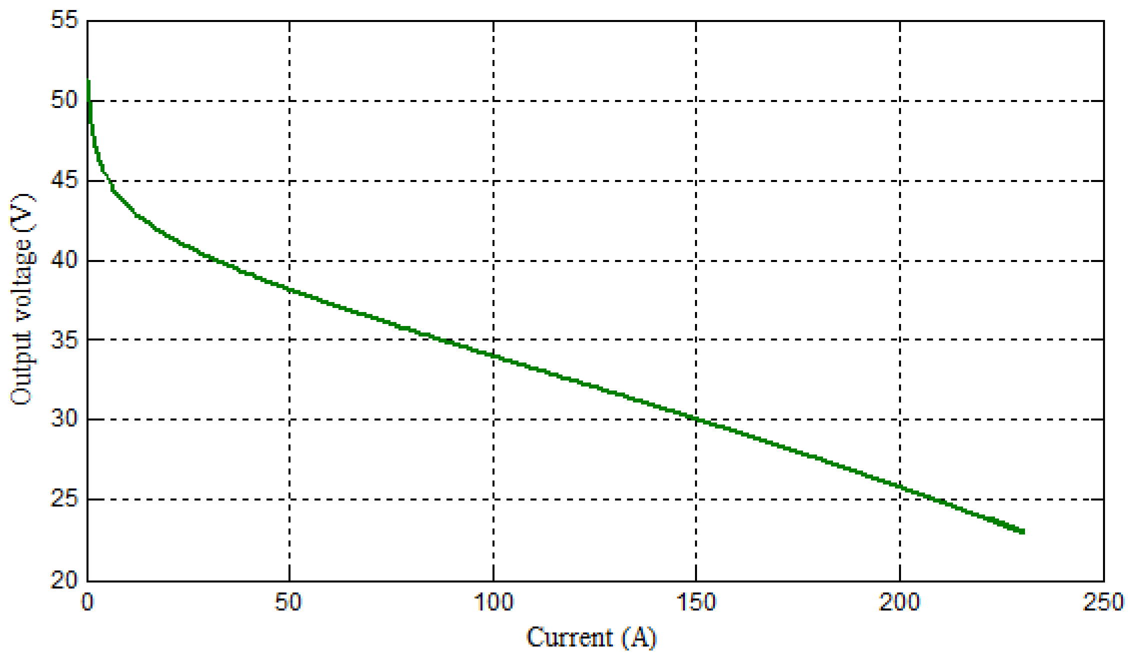


Figure 9. Output voltage versus PEMFC current in T=313 and λ_m =11.

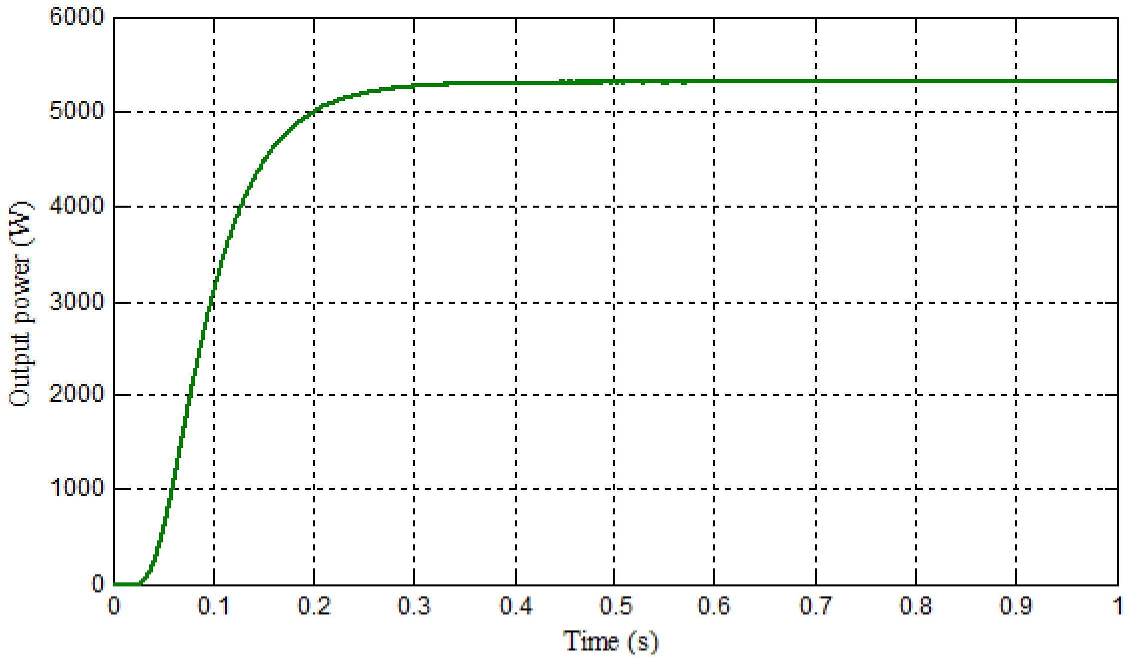


Figure 10. Output power versus time in T=313 and λ_m =11.

Figs. 8 and 9 show the P_I and V_I curves respectively when the proposed strategy is applied to the studied FC system. Fig. 10 shows output power versus time curve in constant condition, T=313 and λ_m =11. It can be seen that optimum power in this condition is 6.15 Kw, which is obtained in acceptable settling time 0.4 sec.

3.6. Case two: step variation of the fuel cell temperature and membrane water content

As section 3.4, we are going to test and compare four MPPT approaches namely PSO, COA, P&O, and the proposed approach in a same FC system. So, in this case, PSO, COA and P&O [14], algorithms have been compared with the proposed MPPT method in abnormal conditions. It is important to notice that the use of PSO algorithm in FC systems unlike photovoltaic systems has not received much attention in the past. Therefore, this algorithm like COA algorithm is a new approach in MMPT context in FC systems, so the results produced from these algorithms can be considered as reference results in future studies. To survey the fast response of the proposed MPPT method in comparison with PSO, COA, and P&O [14], at first, a step changes is applied to the membrane water content while the cell temperature is kept constant and then for the next case, a step changes is applied to the cell temperature while the membrane water content is kept constant.

3.6.1. Step changes of the membrane water content

At first in this section, a step changes is applied to the membrane water content while the cell temperature is kept constant. Fig.11 shows the step changes of the membrane water content applied to the PEMFC system. In this case, the cell temperature is considered constant as *T*=333. Fig. 12 represents the obtained output power versus time.

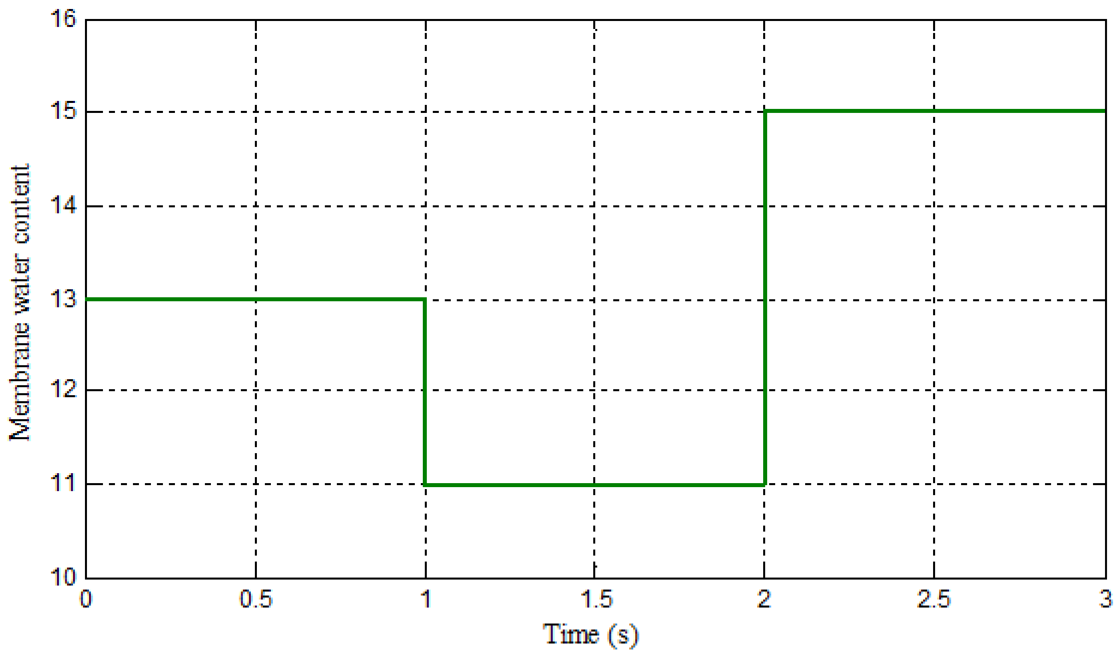


Figure 11. Changes of the membrane water content.

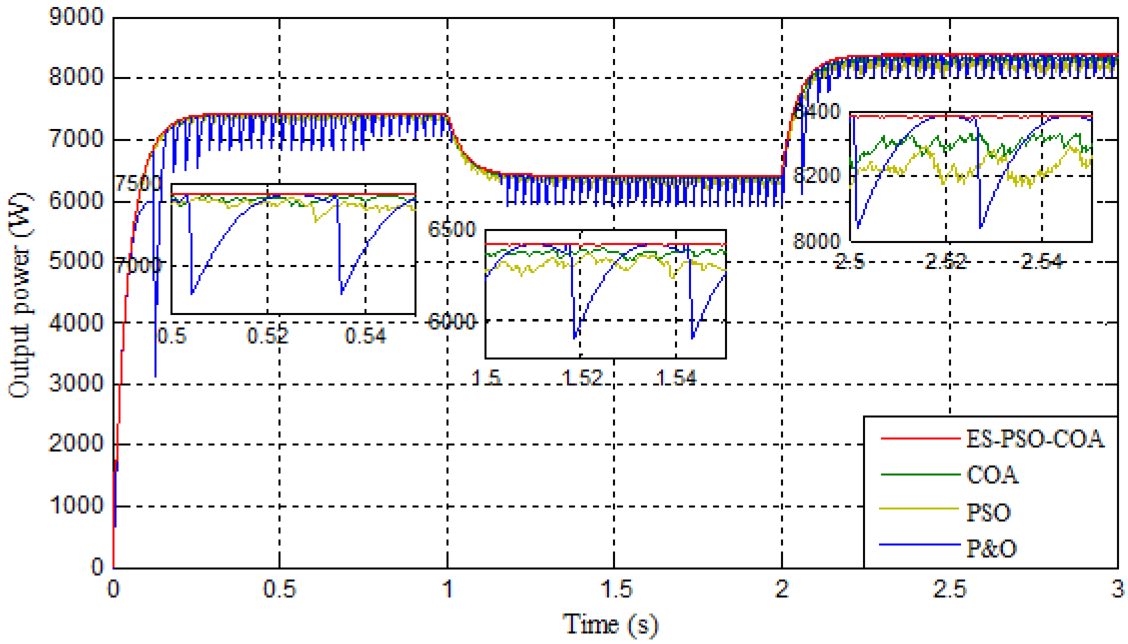


Figure 12. Output power versus time in *T*=333, and under changes of λ_m.

This result confirms the fast and accurate performance of the proposed MPPT method. Furthermore, the standard deviation and mean output power for 1000 recorded samples have been calculated, and its results has been compared with the other conventional optimization algorithms; PSO and COA algorithms based MPP trackers and perturb & observe (P&O) [14] methods, which is shown in Table 4.

Table 4. Numerical results of the proposed approach, COA, and PSO in different λ_m.

Lambda	Proposed approach		COA		PSO		P&O	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
13	7.4305×10^3	1.38	7.3938×10^3	15.83	7.3540×10^3	30.58	7.3074×10^3	155.325
11	6.4148×10^3	1.80	6.3583×10^3	18.11	6.2960×10^3	30.58	6.2945×10^3	146.747
15	8.3832×10^3	1.55	8.2987×10^3	21.44	8.2982×10^3	39.61	8.2978×10^3	101.70

3.6.2. Step changes of the cell temperature

For the second validation in this section, a step changes is applied to the cell temperature while the membrane water content is kept constant. Fig.13 shows the step changes of the cell temperature applied to the PEMFC system. In this case, the membrane water content is considered constant as λ_m =13. Fig. 14 represents the obtained output power versus time.

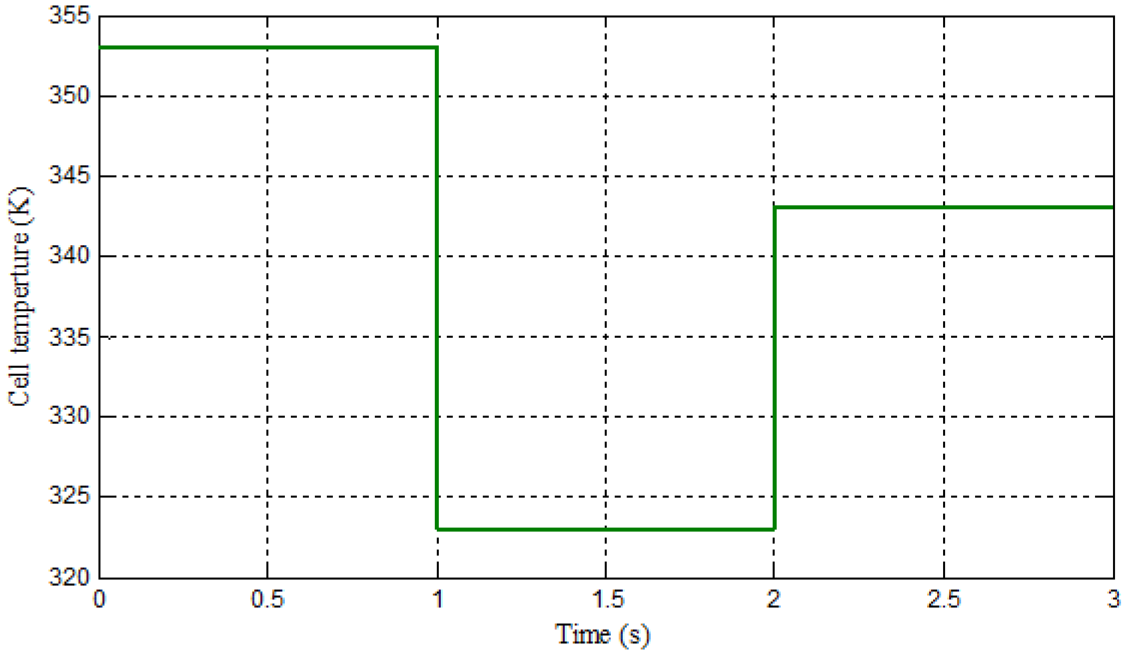


Figure 13. Changes of the cell temperature.

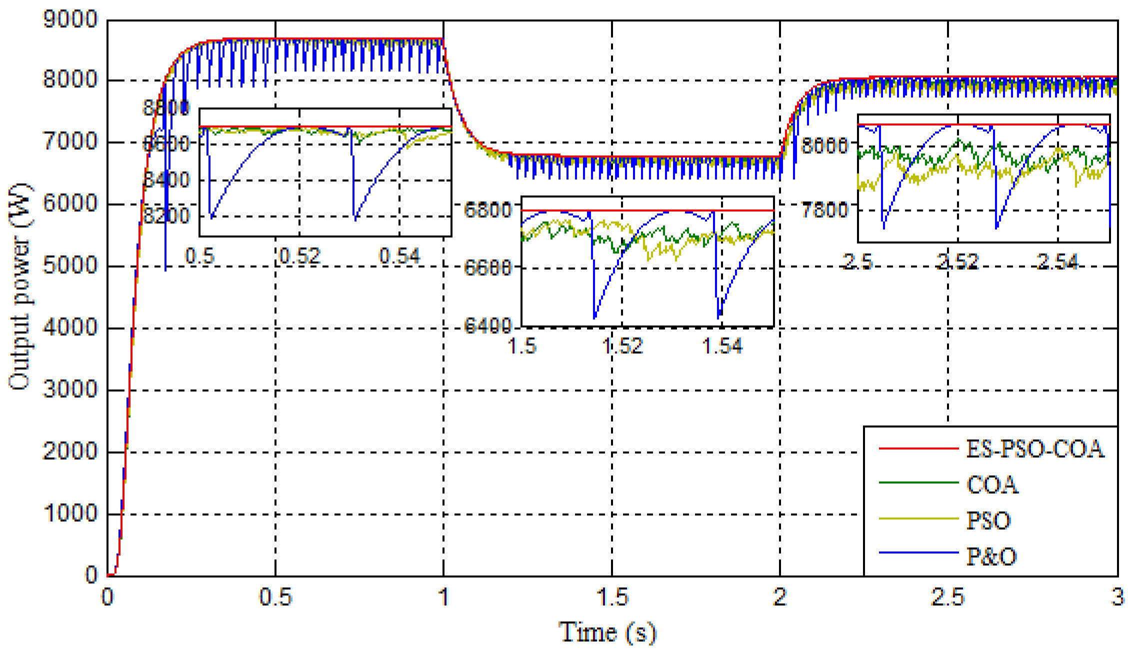


Figure 14. Output power versus time in λ_m =13**,** and under **c**hanges of *T*.

The standard deviation and mean output power for 1000 recorded samples have been calculated, and its results has been compared with the other conventional optimization algorithms; PSO and COA algorithms based MPP trackers and perturb & observe (P&O) method [14], which is shown in Table 5.

Table 5. Numerical results of the proposed approach, COA, and PSO in different *T*.

Temperature	Proposed approach		COA		PSO		P&O	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
353	8.6967×10^3	0.87	8.6612×10^3	18.29	8.6427×10^3	27.95	8.5701×10^3	153.975
323	6.7966×10^3	0.38	6.7240×10^3	23.93	6.7030×10^3	27.67	6.7073×10^3	107.02
343	8.0663×10^3	1.07	7.9583×10^3	25.69	7.9102×10^3	36.67	7.9897×10^3	91.84

As shown in the numerical results of this table obtained from above figures, it is clearly observable that the proposed approach has lower standard deviation than the other algorithms, which leads to reduce the output oscillations in different conditions. This fact is more obvious in high membrane water content. The ability of the proposed approach in decreasing the standard deviation and so improving the output power proves its superiority and sufficiency than the other conventional algorithms.

4. CONCLUSION

In this paper, an intelligent strategy called eagle strategy coupled with particle swarm optimization (PSO) and cuckoo optimization algorithm (COA) is proposed. Eagle strategy is a two-stage strategy that focus in the optimal point intensively, so it reaches higher mean output power and lower standard deviation (SD). This advantages lead to increase the search speed and accuracy (shown in Table 4). These two major factors also lead to generate the accurate and stable output data. So the main advantage of the proposed approach is reducing the oscillation of the output power of the PEMFC by generating the stable set point. This advantage has been shown in Figs. 12 and 14. The other advantage of the ES is that it can use different optimization algorithm in each stage, for instance in [21], the differential evolution optimization algorithm has been used in both stages. According to the simulation results, mean output value and standard deviation of the proposed approach are higher and lower respectively than PSO, COA, and P&O (Tables 3, 4 and 5). The simulation results have been validated the superiority of the proposed approach than PSO, COA, and P&O in any conditions. On the other hand, implementation of COA algorithm as a new algorithm beside the proposed approach can be considered as a reference for future studies in MPPT context in FC systems.

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