IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received November 16, 2019, accepted December 9, 2019, date of publication December 13, 2019, date of current version December 23, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2959547

Recent Coyote Algorithm-Based Energy Management Strategy for Enhancing Fuel Economy of Hybrid FC/Battery/SC System

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ABSTRACT An optimized energy management strategy (EMS) based on a recent coyote optimization algorithm (COA) applied to a hybrid electric power system is proposed in this paper. The proposed hybrid system comprises fuel cell (FC), battery storage bank (BSB) and supercapacitors (SCs). The FC has been selected to be the chief power source to meet the load demand at steady state. Whereas BSB is used as the chief energy buffer and to help the FC during deficit periods and SCs are employed to meet the transient maximum power. The performance of the hybrid electric power system mostly depends on how to distribute the demanded load through different kinds of power sources. Therefore, optimized EMS is highly required to do this job. The key objective of the proposed EMS is to reduce hydrogen consumption by the hybrid system and increase the durability of power sources. To investigate the superiority and validity of COA, a comparison with other approaches is carried based on minimum hydrogen consumption and high energy efficiency. Such methods include external energy maximization strategy (EEMS), particle swarm optimizer (PSO), genetic algorithm (GA), grey wolf optimizer (GWO), grasshopper optimization algorithm (GOA), multi-verse optimizer (MVO), salp swarm algorithm (SSA) and sunflower optimization (SFO). The obtained results confirmed the superiority of the proposed COA. Using COA reduced hydrogen consumption by 38.8% compared to the EEMS method. Based on the minimum hydrogen consumption, the strategies are ranked from the best as following; COA, GWO, SSA, GOA, MVO, GA, PSO, and EEMS.

INDEX TERMS Energy efficiency, fuel cell, supercapacitor, energy management, optimization.

I. INTRODUCTION

Freshwater, energy and the environment are interrelated factors that have become one of the most important and widespread topics in engineering research. Specifically, global warming and resources scarcity have been still the main issues that have been addressed. Therefore, industrial activities and engineering communities start a new era of energy-efficient uses. The environmental issues and economic concerns rise tendency to develop the transportation sector [1]. The transportation sector is mainly depending on fossil fuel and emit greenhouse gases. Therefore, several attempts have been done to increase the usage of the fuel cells (FCs) in transport applications as a green electric power source with zero greenhouse gas emission [2], [3]. Spreading the application of FCs in electric cars, trains and aircrafts protects the surroundings and secure a renewable fuel source for the transport applications [4]. FCs are emerging energy conversion devices that demonstrated numerous features compared to conventional devices such as high energy efficiency, small in size, environmentally safe, long lifetime. . .etc. FCs produce electrical power via chemical reactions in the presence of hydrogen, oxygen, and electrolyte. The proton exchange membrane fuel cell (PEMFC) is considered as the most suitable type to be used in transport application since it has high density in electric power production in conjunction with lower heat generation causing lower temperature that is essential in transport applications.

The low dynamic response is the main disadvantage faces FC in transportation application. It cannot deliver suitable

The associate editor coordinating the review of this manuscript and approving it for publication was Jie Tang.

reactions to unexpected load changes since the gas supply of FC lags behind the load variation [5], [6]. Therefore, FC must be integrated with battery and/or supercapacitor [7], [8]. Battery storage has high energy density; however, it also has some weaknesses. Such weaknesses include low power density, long charging time, high cost and short lifetime. In contrary, SC has high power density and long lifetime [6].

The optimal method to solve the mentioned issues is the utilization of hybrid FC/BS/FC. This topology permits the different power sources to provide their features: FC as the chief steady-state power source, BSB as an energy buffer and SCs as a device for transient maximum power. For achieving such hybridization and reach the main target, an energy management strategy (EMS) is highly required to distribute the load demand among energy sources [6], [9]. The EMS considerably enhances the hydrogen consumption and increase energy efficiency by restricting the operation of the FC to high-efficiency operating points [7]. Numerous traditional EMSs were proposed to manage the load demand among the hybrid system components. Such EMSs include state machine control, fuzzy, PI control, equivalent and external energy maximization strategy (EEMS). In addition to other strategies based on modern optimization.

Wang et al. [10] suggested a management strategy based on the finite state machine for a multi-system comprising battery, fuel cell (FC) and supercapacitors (SC). Energy management based on Proportional-Integral (PI) controller has been presented in Ref. [11] to manage energy between photovoltaic (PV), FCs, batteries, and SCs. In ref. [12], the power estimate of battery and SC is employed for rule energy management strategy, different modes of operation have been analyzed for a hybrid system comprising a battery, SC and FC. *Jiang et al.* [13], presented a dynamic programming approach for minimizing the consumption of energy for hybrid system of FC, battery, and SC to supply power train. *Li et al.* [14] presented energy management based fuzzy logic control for two-hybrid systems, the first one comprises FC and battery and the second one has FC, battery, and ultracapacitors (UCs) for supplying an electric vehicle. Adaptive neuro-fuzzy inference system (ANFIS) has been presented in Ref. [15] to optimally manage the power between FC, battery employed to supply unmanned electric vehicle. *Chen et al.* [16] introduced two layers energy management approach based on wavelet transformation and radial basis neural network to optimize the energy distribution in EVs. An energy management technique based on wavelet transform algorithm was presented in Ref. [17] for managing the power between FC, UCs, and battery for supplying EVs. *Djerioui et al.* [18] introduced grey wolf optimizer (GWO) to optimally manage a hybrid source of FC, SC for EVs. An equivalent consumption minimum strategy (ECMS) has been introduced in Ref. [6] using sequential quadratic programming to manage the power between FC, battery, and SC for EVs. *Marzougui et al.* [19] presented a strategy combining three approaches for energy management between FC, UC, and battery supplying EVs, the approaches are fuzzy logic control, rule-based algorithm and flatness control. Fathy *et al.* [4] introduced a new approach based salp swarm algorithm (SSA) to optimally manage the energy between FCs, batteries, and SCs with considering hydrogen consumption as an objective function. *Li et al.* [20] analyzed the energy management of a hybrid source of FC and SCs for supplying excavator based on three approaches of dynamic programming, model predictive control and minimum principle of Pontryagin considering hydrogen consumption as the objective function. *Zhao et al.* [21] presented different metaheuristic optimization approaches for managing the energy of the fuel cell hybrid system for supplying aircraft. *Yu et al.* [22] designed a hybrid FC, battery and SCs to supply EVs optimally such that minimizing the system cost. Rule-based distribution technique has been employed in Ref. [23] to manage the energy of a hybrid generating system. Additionally, Bays Monte Carlo algorithm has been introduced to estimate the power of batteries and SCs. *Thounthong et al.* [24] presented energy management for hybrid FC, battery and SC for EVs' applications. *Han et al.* [25] introduced two levels of energy management for PV, FC, and battery incorporated in DC microgrid. Different approaches of energy management strategies employed in managing the energy in EVs powered by fuel cells have been reviewed in Ref. [3]. *Bendjedia et al.* [26] designed an energy storage system (ESS) representing FC and another source for supplying light vehicle by investigating three approaches for energy management. In Refs. [6], [27], different energy management strategies have been presented for EVs powered by FC. *Bizon* [28] introduced an adaptive energy management approach based two-dimension function representing the economics of fuel of FC hybrid system. *Li et al.* [29] presented combined fuzzy logic control and wavelet transformation to manage the energy of hybrid tramway optimally.

The main contribution of this research is proposing an optimized EMS for reducing hydrogen consumption and slow down the FC performance degradation. According to the No Free Lunch theorem [30], no single optimizer can solve all optimization problems, which means that new optimizers are still welcome in the research area of energy management. A recent optimizer called coyote optimization algorithm (COA) is presented by *Pierezan* and *Coelho* in 2018 [31]. The main advantage of COA is providing a new mechanism to balance the exploration and exploitation during the optimization procedure. This urges the authors to use it for the first time to optimally manage the load demand among power sources in hybrid FC/BS/SC.

Most of reported approaches have some shortcomings in terms of complicated structure of energy management strategy, EMS, and requirement of large efforts in implementation, need high initial state of charge, SOC, for battery and SC with excess data especially for methods employed ANFIS. Additionally, some employed heuristic optimization approaches in EMS may fall in local optima. In this paper, we considered all these defects and proposed a simple constructed EMS based on reliable heuristic approach of coyote optimization algorithm (COA), as it provides a balance between the exploration and exploitation during the optimization procedure, this feature prevents the algorithm to fall in local optima.

II. PROBLEM FORMULATION

In hybrid FC/BS/SC, it is important to optimally manage the energy between the energy elements for enhancing the hybrid system performance. This job can be achieved by minimizing the consumption of hydrogen in the proposed system with keeping the state of charge (SOC) for both BS and SC within their acceptable limits. The core idea of external energy maximization strategy (EEMS) is based on minimization of hydrogen consumption through maximizing the demand of BSB and SCs with achieving their constraints. EEMS is characterized by its simplicity as it only requires the cost function of BS and SC and it doesn't require the calculation of battery energy which is usually determined empirically [32]. The configuration of EEMS is shown in Fig. 1. Considering Fig. 1, the inputs to the EEMS are the state of charge (SOC) of BSB and DC bus voltage. The outputs are the reference power of BSB and SCs charge/discharge voltage (ΔV). The power of BSB is compared with the load demand to estimate the reference power of FC through the FC current (I_{FC}^{*}). SCs state (charge/discharge) is evaluated by comparing the sum of its voltage and reference voltage of DC bus ($V_{\mathrm{dc\_ref}}$) with the actual DC bus voltage.

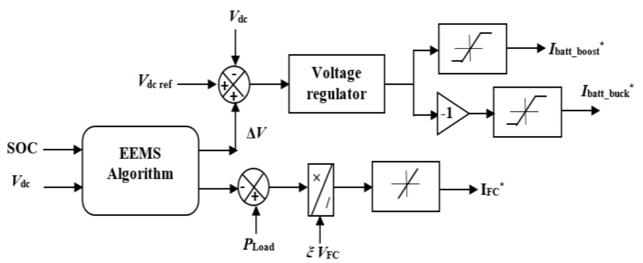

FIGURE 1. EEMS configuration.

In the EEMS optimization problem, two variables have to be evaluated. They are BSB power and the charge/discharge voltage of the SCc; $x = [P_{batt}, \Delta V]$. The objective function to be maximized is the energy supplied by BSB and SCs during a certain time interval, it can be formulated by the following [32]:

$$Maximize\ J = -\left(P_{batt}.\Delta T + \frac{1}{2}C_r.\Delta V^2\right) \quad (1)$$

Subjected to

$$P_{batt}\Delta T \leq \left(SOC - SOC^{\min}\right) V_{batt} Q \quad (2)$$

While the parametric inequality constraints of battery power and DC bus voltage are described as follows:

$$\begin{aligned} P_{batt}{}^{\min} \leq P_{batt} \leq P_{batt}{}^{\max} \\ V_{dc}{}^{\min} \leq V_{dc} \leq V_{dc}{}^{\max} \end{aligned} \quad (3)$$

where P_{batt} is the battery delivered power during sampling time of ΔT, C_{r} is supercapacitor rated capacitance, $V_{\mathrm{dc}}^{\min}$ and $V_{\mathrm{dc}}^{\max}$ denote the boundaries of buss DC voltage, V_{batt} denotes voltage of BS and Q is BS capacity.

The conventional EEMS uses *fmin* function from Matlab toolbox. Therefore, to enhance the performance, *fmin* is replaced by a modern optimization algorithm. During the optimization process, the decision variables are FC output power, P_{FC}, the battery output power, P_{batt}, and the battery state of charge (SOC). The lower and upper bounds of the variables under consideration are selected as, $P_{FC}^{min} = 850$ W, $P_{FC}^{max} = 8800$ W, $P_{batt}^{min} = 1500$ W, $P_{batt}^{max} = 3400$ W, $SOC^{min} = 60$; $SOC^{max} = 90$. The suggested strategy used COA optimizer for maximizing the objective function in equation (1) with the related constraints explained in equation (2). Fig. 2 illustrates the suggested optimization outline. Both battery SOC and SC voltage are fed to the proposed EMS based COA, while the outputs are the battery reference power and charge/discharge voltage of the SC which are compared with the load and the reference SC voltage. The mismatch between the SC voltage and reference one is modified via proportional integral, PI, controller which feeds the battery converter with the required current. on the other hand, the difference between the battery power and the demand is converted to the reference FC current.

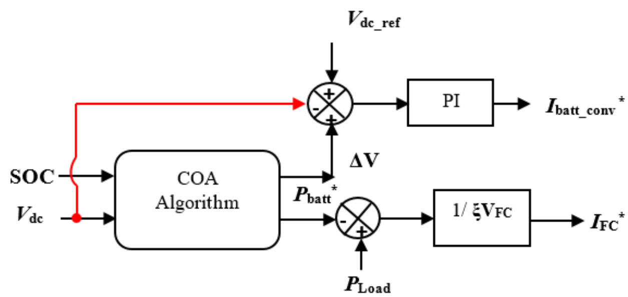

FIGURE 2. The suggested optimization configuration.

III. A BRIEF OVERVIEW ON OPTIMIZATION ALGORITHMS

A. PARTICLE SWARM OPTIMIZER

PSO simulates behavior of known animal social like fish schooling and bird flocking [33], [34]. It has two stages to have in order to find the optimal solution. At first, each particle shares its information with other particles after moving in their direction. They can learn how to update their direction after each iteration and tune the parameters. In the literature, PSO has been used as an effective tool to solve many optimization problems, including optimal allocation of electric vehicle charging station and distributed renewable resource in power distribution networks [35] and global maximum power point tracking of photovoltaic system under partial shading [36], [37].

B. GENETIC ALGORITHM

GA is a search heuristic algorithm. The core idea of GA is extracted from Darwin's theorem of natural evolution.

GA reflects the process of natural selection where the fittest individuals are chosen to continue in the next generation. During the optimization process, five stages were taken into consideration. Such stages include; initialization, fitness function, selection, crossover, and mutation [38].

C. GREY WOLF OPTIMIZER

GWO optimizer inspired by the natural mechanism of animals [39]. It solves optimization problems through some stages. Firstly, it searches for some animal as prey. Next, it surrounds the possible prey(s) by exploitation, doing a local search for finding the border of sample space. Lastly, it attacks the prey, doing a local search to find the best value within a new area.

D. GRASSHOPPER OPTIMIZATION ALGORITHM

Grasshopper Optimization Algorithm (GOA) is proposed by Saremi *et al.* [40]. In this method, Grasshopper are insects. They are deemed a pest because of their harm to crop production and agriculture. Even though grasshoppers are frequently seen separately in nature, they become involved one of the biggest swarm of whole creatures. The swarm size sometimes becomes a continental scale and a nightmare for farmers. Millions of nymph grasshoppers' leap and shift as rollers. They eat almost all plants. When nymphs become adults, they form a swarm in the air. This is how grasshoppers travel over large distances.

E. MULTI-VERSE OPTIMIZER

MVO is considered as one of the recent optimizer's developed by Mirjalili theory [41]. The core idea of MVO is based on three concepts in cosmology: white hole, black hole, and wormhole. MVO divides the search process to two main stages: exploration and exploitation. The concepts of white hole and black hole are employed for exploring search spaces by MVO. In contrary, the wormholes are used to explore the search spaces. More details about the mathematical model of MVO can be found in [41].

F. SALP SWARM ALGORITHM

Motivated by exploration and foraging attitude of salp in the deep ocean, Mirjalili *et al.* [42] reported a novel optimization technique, named SSA. These creatures form a close chain called swarm or salp chain. This chain comprises of a leader salp and a group of followers, which attempt to find the best region of food via this search method. Likewise, the algorithm is initialized with an initializing matrix of $n \times dim$, which represents salps' positions, where n denotes the agents and dim is the decision variables. This is a recursive process, where the position of each salp is updated, as per the information given by the leader, for devouring the best food (F).

G. SUNFLOWER OPTIMIZATION

Sunflower optimization (MFO) was presented by *Gomes et al.* [43] and motivated from the motion of sunflower with the sun movement. At every day, sunflowers wake and follow the sun like the clock's needles. Sunflower motion follows inverse square law radiation which states the radiation intensity is inversely proportional to the square of the distance. When the distance between the plant and the sun is less, the amount of received radiation becomes great and vice versa. The first step in MFO is initializing a population includes individuals, the fitness function of each individual is calculated to determine which individual will be switched to the sun.

IV. PROPOSED COYOTE OPTIMIZATION ALGORITHM

Coyote optimization algorithm (COA) was first proposed by *Pierezan* et al. in 2018 [31], the idea of such a metaheuristic algorithm is motivated from *canis latrans* species that live in North America. COA is interested in acting the coyotes' social society and its acclimation to the environment. The main advantage in COA algorithm is to maintain a balance between exploration and exploitation phases in the optimization process. COA is unlike GWO as it does not care of hierarchy and hegemony rules followed in these animals. Additionally, it doesn't depend on only hunting preys followed in GWO but also the social structure and experiences interchange performed by the Coyotes. They are characterized by cooperative features as they move toward the prey in a group while they have a desire to devour it individually. Coyotes have a strong sense of smell by which the prey location can be identified. In the hunting process, Coyotes attacks they prey in a group, this action requires the agents to update their positions to better ones. When Coyotes' hitting their adversaries, it is well prepared with a threat probability and it surges an excessive random distance away from its current position. The population initiated in COA is divided into N_p packs with N_c coyotes, the approach begins with initializing coyotes' global population, the social condition, soc, of c^{th} coyote in p^{th} pack can be initialized as follows:

$$soc_{c,j}^{p,t} = lb_j + r_j.\left(ub_j - lb_j\right) \tag{4}$$

where lb_j and ub_j are the lower and upper limits of variables to be designed and r_j is a random number in the range [0, 1]. The adaptation of the coyotes in the present social conditions is represented as a fitness function which can be calculated as follows:

$$fit_c^{p,t} = f_c^{p,t}(soc_c^{p,t}) \tag{5}$$

At the beginning of the algorithm, the coyotes are randomly distributed to packs, they may leave their packs or join to another one, this action can occur with a probability of,

$$P_e = 0.005.N_c^2 \tag{6}$$

The process of transferring the coyotes between the packs helps in increasing the populations' interactions with enhancing their cultures. One alpha is selected from three alphas in COA and given as follows:

$$alpha^{p,t} = \left\{soc_c^{p,t} \left| \arg_{c=\{1,2,\ldots,N_c\}} \min f\left(soc_c^{p,t}\right)\right.\right\} \tag{7}$$

In COA, it is assumed that all coyotes are organized adequately to share the social culture. Therefore, the coyotes' information are linked and computed as cultural tendency as follows:

$$cult_j^{p,t} = \begin{cases} O^{p,t}_{\frac{(N_c+1)}{2},j} & N_c \text{ is odd} \\ \dfrac{O^{p,t}_{\frac{N_c}{2},j} + O^{p,t}_{(\frac{N_c}{2}+1),j}}{2} & otherwise \end{cases} \tag{8}$$

where $O^{p,t}$ is the ordered social conditions of coyotes in park p at t^{th} time instant. The ages of coyotes, $age_c^{p,t}$, are calculated in COA as the birth of new one is represented by combining randomly selected two parents' social conditions with considering the influence of environment as follows:

$$pup_j^{p,t} = \begin{cases} soc^{p,t}_{r_1,j} & rnd_j \prec P_s \text{ or } j = j_1 \\ soc^{p,t}_{r_2,j} & rnd_j \prec P_s + P_a \text{ or } j = j_2 \\ R_j & otherwise \end{cases} \tag{9}$$

where $soc_{r1,j}{}^{p,t}$ and $soc_{r2,j}{}^{p,t}$ are the social conditions of two random coyotes r_1 and r_2 in the p^{th} pack at time t, j_1 and j_2 are two dimensions of the problem which are selected randomly, P_s is the probability of scatter, P_a is the probability of association and R_j is a random number in the range of variables' bounds. Both P_s and P_a lead the cultural variety of the coyotes from the pack, they can be calculated as follows:

$$P_s = {}^{1}\!/_{D} \tag{10}$$

$$P_a = {}^{(1-P_s)}\!/_{D} \tag{11}$$

where D is the problem dimension, inside the pack, there are some rules control the processes of birth and death of the coyotes, two parameters are presented in COA for simulating such rules which are the solution groups representing the worst fitness function, ω, and the coyotes' number in such group, φ. Flowchart given in Fig. 3 shows the governing rules for such process. The cultural interaction in the pack is simulated by assuming that the coyotes are under alpha effect, δ_1, and pack effect, δ_2, which can be calculated as follows:

$$\delta_1 = alpha^{p,t} - soc^{p,t}_{cr1} \tag{12}$$

$$\delta_2 = cult^{p,t} - soc^{p,t}_{cr2} \tag{13}$$

where c_{r1} and c_{r2} are random coyotes. The social condition of the coyote is updated based on the alpha and pack effects as follows:

$$soc_c^{p,t,new} = soc_c^{p,t,old} + r_1.\delta_1 + r_2.\delta_2 \tag{14}$$

The updating process of the social condition is performed according to the following condition:

$$soc_c^{p,t+1} = \begin{cases} soc_c^{p,t,new} & fit_c^{p,t,new} \prec fit_c^{p,t} \\ soc_c^{p,t} & otherwise \end{cases} \tag{15}$$

The steps followed in COA are summarized in the flowchart shown in Fig. 4.

The proposed solution methodology incorporated COA is shown in Fig. 5. At the beginning, a population matrix of size

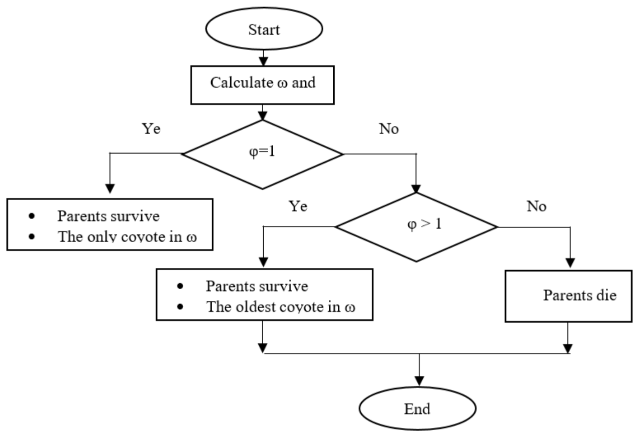

FIGURE 3. Birth and death rules followed in COA.

$N_p \times dim$ is initialized including probable solutions for BSB power and the charge/discharge voltage of the SC. Each row of the population matrix represents a probable solution for the problem. For each row, the steps of COA given in Fig. 4 are performed with observing the Hydrogen consumption for each pack. The pack with the minimum hydrogen consumption is selected as the best solution.

TABLE 1. Electrical specifications of the system under study.

Specifications of FC	
Rated current (A)	250
Rated voltage (V)	41.15
Number of cells	65
%Efficiency	50
Operating temperature (° C)	45
Air flowrate (lpm)	732
Fuel pressure (bar)	1.16
Air pressure (bar)	1
Specifications of battery	
Rated voltage (V)	48
Capacity (Ah)	40
Maximum capacity (Ah)	40
Full charged voltage	55.88
Rated discharge current (A)	17.4
Internal resistance (Ω)	0.012
Specifications of SC	
Rated capacitance (F)	15.6
Series resistance (Ω)	0.15
Rated voltage (V)	291.6
Surge voltage (V)	307
Number of capacitors in series	108
Number of capacitors in parallel	1
Number of layers	6

V. RESULTS AND DISCUSSION

The system under study comprises a hybrid generating source of a fuel cell (FC), battery and supercapacitor (SC), the Simulink/Matlab model is shown in Fig. 6. The system is designed to supply a load of aircraft with a load profile shown in Fig. 7. Table 1 shows the specifications of the system component, the system comprises proton exchange

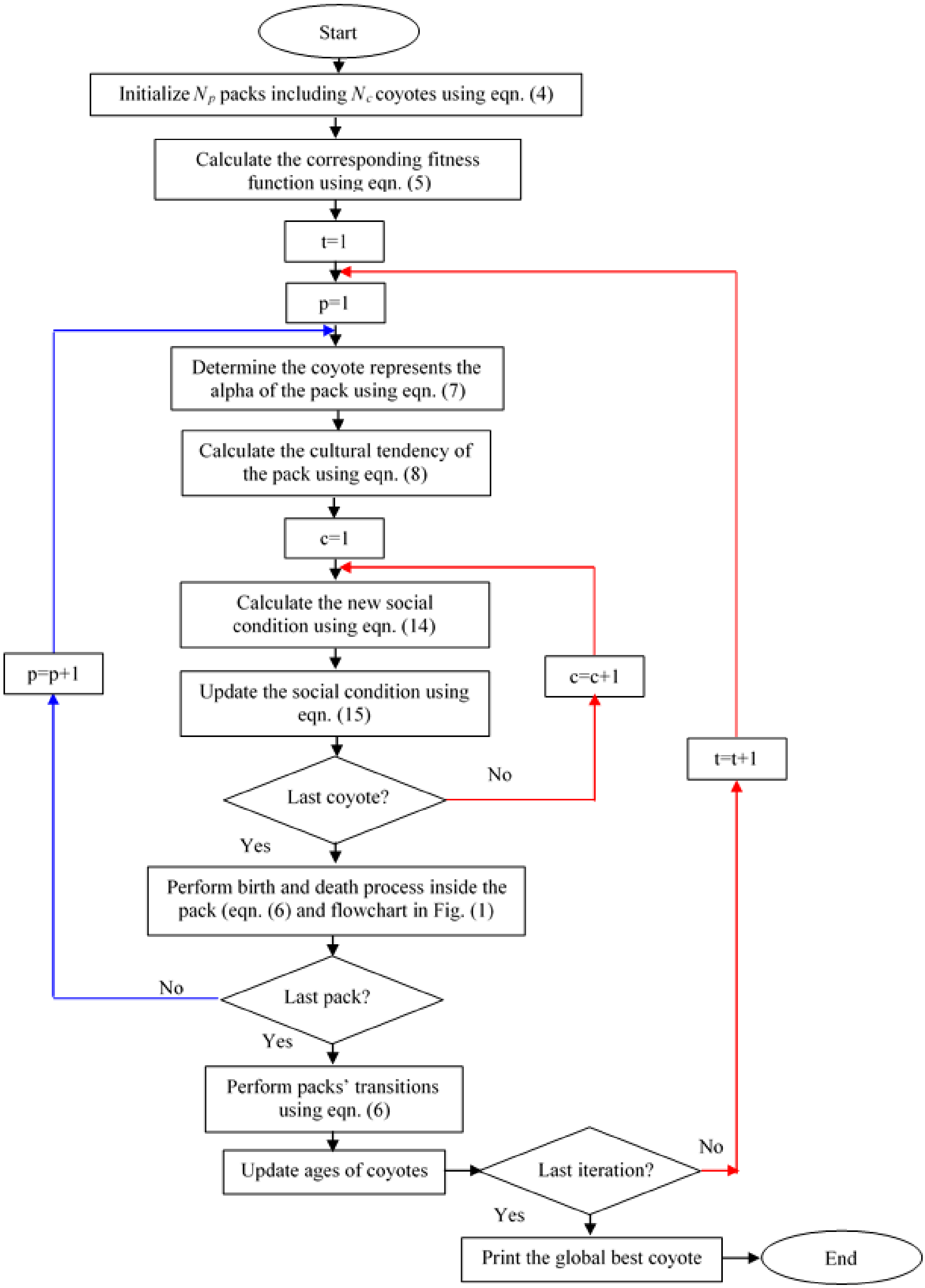

FIGURE 4. COA flowchart.

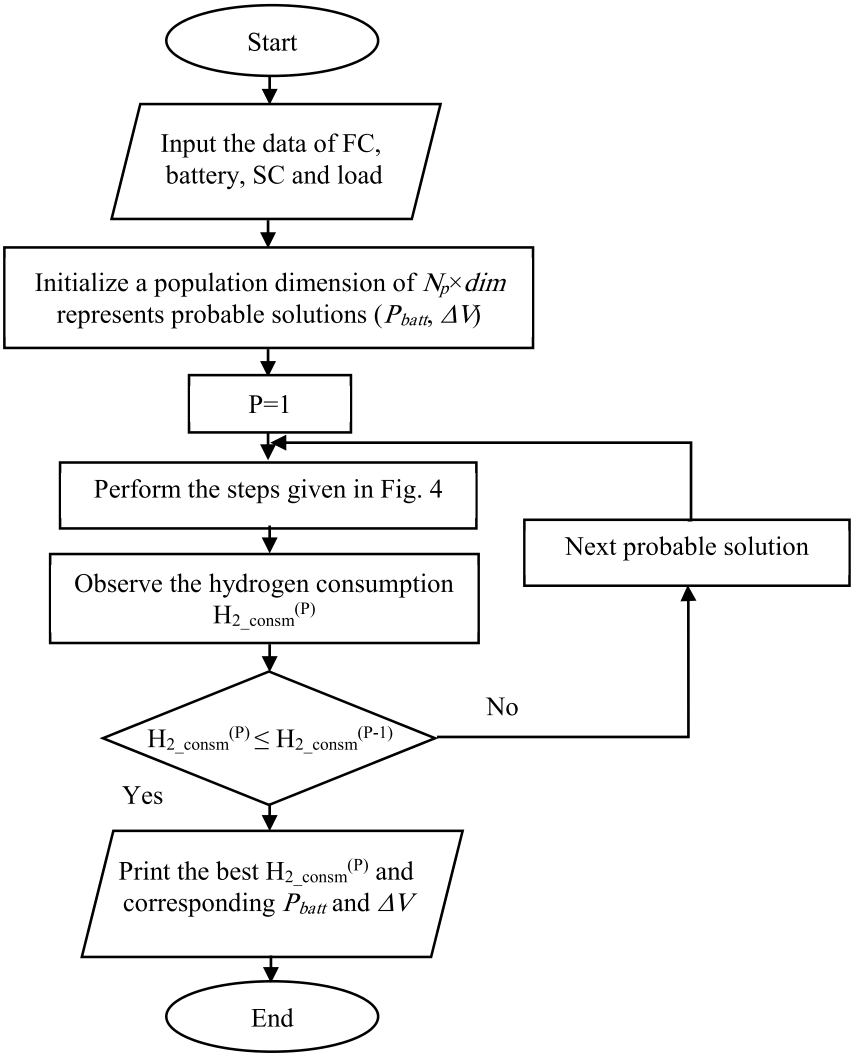

FIGURE 5. The proposed methodology incorporated COA.

membrane fuel cell (PEMFC) of 10 kW power, its terminal voltage is 30-60 V, battery of type Li-ion with rated voltage of 48 V and 40 Ah capacity and 15.6 F, 291.6 V SC stack with six cells connected in series, each one has 48.6 V, boost converter of 12.5 kW power is employed to regulate the terminal voltage of PEMFC. Additionally, two converters are used with battery, 4 kW boost and 1.2 kW buck converters, for regulating charging and discharging processes. To avoid overcharging of both battery and SC, 15 kW protecting resistance is used in the proposed system. An inverter of 15 kVA, 240 V/200 V and 400 Hz frequency is employed to supply the load of aircraft. Referring to the Simulink model of the hybrid system shown in Fig. 6, the reference FC current is supplied to boost converter to extract its maximum value, while the reference current of the battery is supplied to the two converters at its terminal to generate battery reference voltage and DC voltage during the discharging process, V^*_{Batt} and V_{DC2}. The proposed coyote optimization algorithm is represented in Simulink model with a block named COA, the battery state of charge (SOC) and load profile are fed to the COA block then it gives the reference FC current, I^*_{FC}, and reference battery current, I^*_{batt}. The objective of the proposed COA is minimizing the consumption of hydrogen. Table 2 shows the controlling parameters of the proposed COA. To confirm the reliability of the proposed methodology, comparative study with other metaheuristic optimization approaches, external energy maximization strategy (EEMS), particle swarm optimization (PSO), genetic algorithm (GA), grey wolf optimizer (GWO), grasshopper optimization algorithm (GOA), multi verse optimizer (MVO), salp swarm optimizer (SSA) and sunflower optimizer (SFO), is performed. The approaches are selected as they are the same in nature inspired swarm optimization. The optimal hydrogen consumption obtained via the proposed COA in comparison with other approaches are tabulated in Table 3. It's clear that the minimum H_2 consumption is 19.3778 gm obtained via the proposed COA while the worst value is 31.6774 gm obtained via EEMS. Fig. 8 shows the bar-chart of the optimal H_2 consumption obtained via COA compared to other approaches.

The hybrid FC, battery, and SC presents an emergency source used in the landing of the aircraft (load), first, the load is supplied via 3-phase source and during this period the

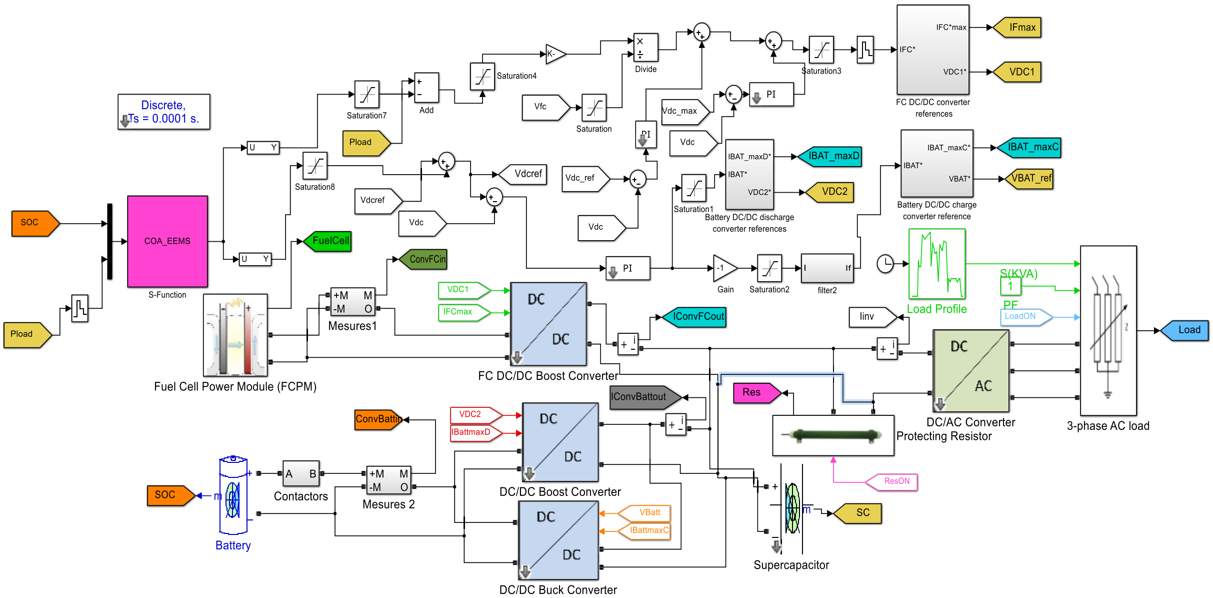

FIGURE 6. Hybrid FC/battery/SC Simulink model.

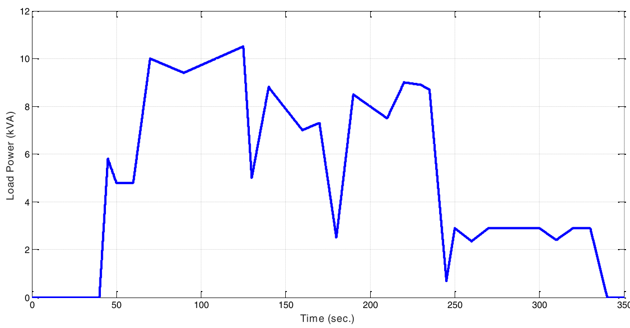

FIGURE 7. Load profile.

TABLE 2. The proposed COA controlling parameters.

Parameters	Value
Maximum Iteration	300
Number of packs	100
Number of coyotes	5

FC is employed to recharge the battery until it reaches to its nominal power. When the main source is interrupted, the hybrid system is employed to supply the essential loads. The SC is discharged and its terminal voltage becomes less than the reference voltage, at this situation battery supplies power to regulate the DC bus voltage to its reference values. During this situation, FC supplies the total power to load and also recharge the SC. When FC reaches to its maximum power, the battery is employed to supply extra power to load until it reaches to its maximum power then SC shares the load. The time response of H_2 consumption obtained via the proposed COA in comparison with the others is shown in Fig. 9. While the variation of consumed hydrogen, in Im, with time obtained via all studied approaches is shown in Fig. 10. The responses confirmed the superiority of the proposed COA as it provides the minimum H_2 consumption compared to the others.

TABLE 3. Hydrogen consumption obtained via the proposed COA and other approaches.

Methodology	H_2 consumption (gm)
EEMS	31.6774
PSO	25.4348
GA	21.4513
GWO	19.4000
GOA	19.4176
MVO	19.4308
SSA	19.40
SFO	19.4817
Proposed COA	19.3778

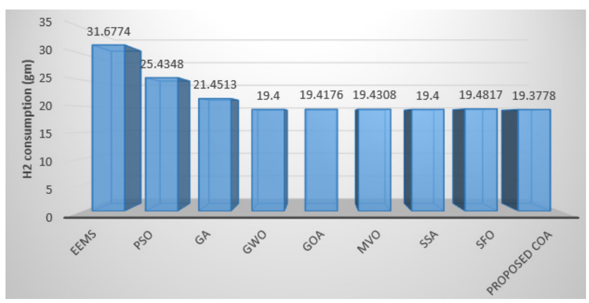

FIGURE 8. Bar-chart of optimal Hydrogen consumption obtained via the proposed COA and other approaches.

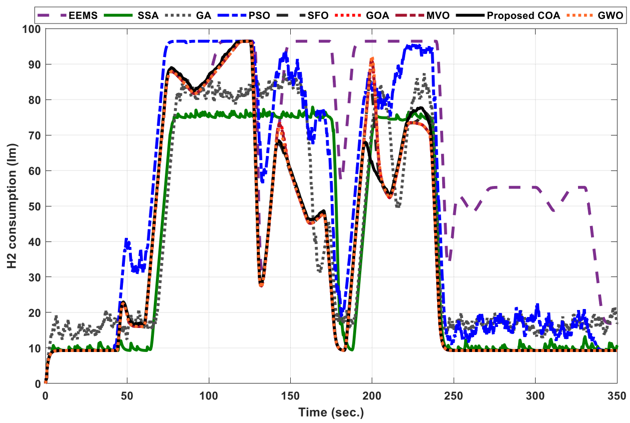

FIGURE 9. Variation of hydrogen consumption for all studied approaches.

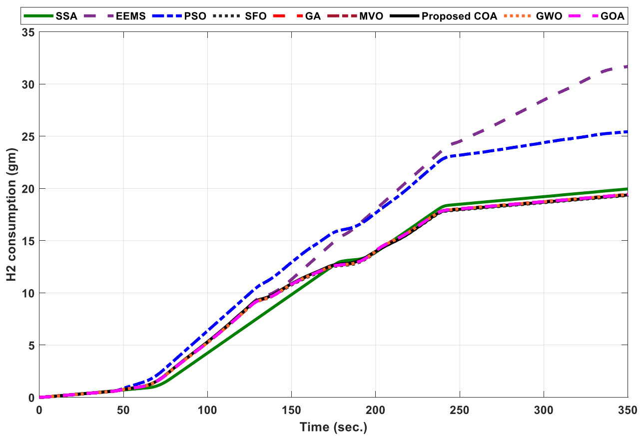

FIGURE 10. Time response of H2 consumption in gm obtained via COA compared to the others.

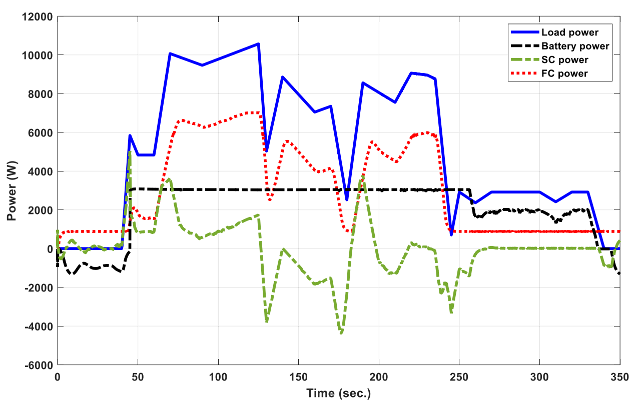

FIGURE 11. Variation of FC, battery, SC and load powers with time.

The variations of FC, battery and SC powers with time are shown in Fig. 11, in addition to the load profile. The response confirmed that FC represents the main emergency source while the battery and SC act as auxiliary suppliers employed to cover extra load in case of FC extracts its maximum power.

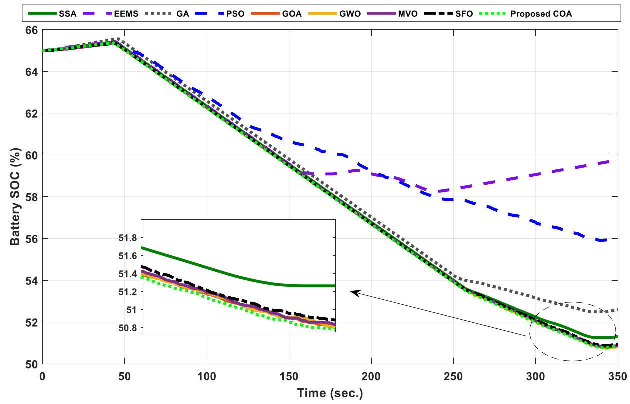

FIGURE 12. Time response of battery SOC obtained via all studied approaches.

Fig. 12 shows the battery SOC variation with time. At the beginning of the simulation, the battery SOC is nearly equal to 55% (nearly half fully charged), then the SOC is increased as at this period, FC is employed to charge the battery. At t = 40 sec., the main source is interrupted and the hybrid system is used to supply load, therefore; the battery SOC begins in decreasing until the end of the simulation. Referring to Fig. 12, the minimum SOC is obtained via the proposed COA, this confirmed the dependency on the battery to cover the load is more than dependence on fuel cells, resulting in less hydrogen consumption and this confirms the preference of the proposed method in minimizing the amount of H_2 consumption compared to the other approaches.

Additionally, the efficiency of the proposed COA compared to the others are calculated and tabulated in Table 4, the efficiency is calculated via dividing the average load demand by the average generated power from the hybrid system. The proposed approach succeeded in achieving the highest efficiency of 82.09% while the worst efficiency is 68.27%obtained via GWO.

TABLE 4. Efficiency of the proposed COA compared to other approaches.

Strategy	Efficiency (%)
EEMS	74.15
PSO	73.6
GA	80.20
GWO	68.27
GOA	78.31
MVO	80.34
SSA	81.22
SFO	79.47
Proposed COA	82.09

Finally, one can get that, the obtained results confirmed the superiority and efficiency of the proposed COA in solving the problem of H_2 consumption of hybrid emergency FC, battery and SC employed to supply aircraft load in landing situations.

VI. CONCLUSION

An efficient energy management strategy (EMS) based on a recent coyote optimization algorithm (COA) applied to a hybrid electric power system is proposed in this research paper. Such system comprises fuel cell (FC), battery and supercapacitor. The key objective of the suggested EMS is to reduce consumed hydrogen of the system. To test the superiority and validity of COA, a comparison with other methods is carried out. Such methods include external energy maximization strategy (EEMS), particle swarm optimizer (PSO), genetic algorithm (GA), grey wolf optimizer (GWO), grasshopper optimization algorithm (GOA), multi-verse optimizer (MVO), salp swarm algorithm (SSA) and sunflower optimization (SFO). The obtained results confirmed the superiority of the proposed COA. Using COA reduced hydrogen consumption by 38.8% compared to the EEMS method. Based on the minimum hydrogen consumption, the strategies are ranked from the best as following; COA, GWO, SSA, GOA, MVO, GA, PSO, and EEMS. In future works, it's recommended to consider the system overall cost in optimization process of hybrid FC/Battery/SC with EMS.

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