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Coyote Optimization Algorithm-Based Energy Management Strategy for Fuel Cell Hybrid Power Systems

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Abstract: This research proposes an improved energy management strategy (EMS) for a fuel cell hybrid power system for an electric aircraft based on a recently developed coyote optimization algorithm (COA). The suggested hybrid system consists of fuel cells and an energy storage system (ESS) to supply the required load in stable conditions. The distribution and performance of the hybrid electrical power system are determined by various energy sources. Consequently, having the best energy management system is essential for completing this work. The suggested EMS's main objectives are to reduce hydrogen energy utilization and increase power source longevity. The proposed coyote optimization algorithm with external energy maximization strategy (COA-EEMS) and coyote optimization algorithm with equivalent consumption minimisation strategy (COA-ECMS) are tested with the help of the Opal-RT 5700 real-time HIL simulator and MATLAB/Simulink. The proposed algorithms confirm their robustness and higher efficiency by minimizing hydrogen fuel consumption compared to existing algorithms. The merits of the proposed algorithms are presented in detailed and compared with existing algorithms.

Keywords: coyote algorithm; mine blast algorithm; salp swarm algorithm; energy management system; optimal hydrogen consumption; fuel cell hybrid electric aircraft

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1. Introduction

Atmosphere, water, and energy are three interconnected aspects that have manifested as some of the most significant and pervasive research areas in engineering. Specifically, resources are still in short supply and global warming is still the main problem that has been addressed. Consequently, industrially, a new era of activities and engineering communities' energy-efficient usage has been entered. Environmental and financial concerns increase the propensity to advance the transport sector (TS) [1]. The TS creates greenhouse gases (GHGs) and is mostly dependent on fossil fuels. As a result, several efforts have been made to promote the use of fuel cells (FCs) in transportation applications as a green energy source emitting no GHGs [2,3]. Fuel cells are now employed in automobiles, buses, tramways, trains, and aeroplanes [4]. In contrast to conventional internal combustion engines, they provide electrical power with high efficiency, reduced noise, and almost no emissions.

Manufacturers of more-electric aircraft (MEA) are working to replace the emergency power system, which comprises a ram air turbine or an air-driven generator, with fuel-cell devices as the first step towards creating greener aircraft [5–7]. The emergency power system will work better as a result, especially at low aircraft speeds and altitudes. It is necessary to hybridize fuel cells with modern energy storage technologies, such as lithium-ion batteries or supercapacitors, to increase the dynamics and power density of fuel-cell systems. As some of the load is supplied by the batteries or supercapacitors, this hybridization enables the fuel-cell system to be optimized to achieve improved fuel economy and performance. An energy management strategy (EMS), which distributes the load power across the energy sources, enables this optimization. Such an EMS should be designed to maximize fuel efficiency while ensuring that each energy source performs within its capabilities. Additionally, as much as is feasible should be done to minimize the influence of the EMS on the entire hybrid power system's life cycle.

Figure 1 shows the proposed COA-based EMS for a fuel cell emergency power system for an electric aircraft. The hybrid power system is designed based on the power and energy requirements for a typical emergency landing scenario. In this paper, a representative emergency landing cycle provided by Bombardier Aerospace, is considered for all analyses. The emergency load model is represented by a three-phase controlled current source, where the load current is obtained from the three-phase apparent power (in kilo volt-amperes) load profile, the power factor, and the nominal line voltage.

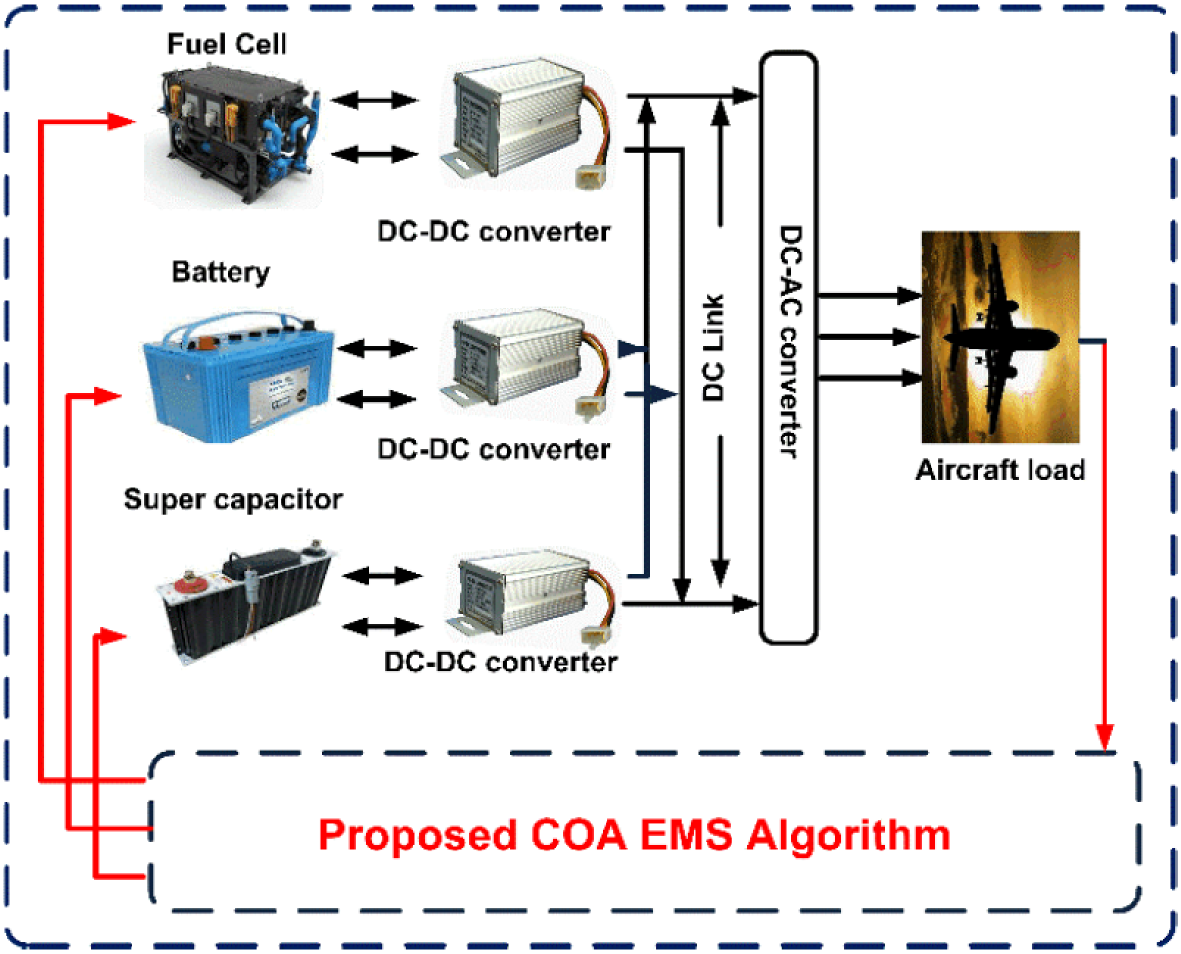


Figure 1. The overall structure for a fuel cell emergency power system for an electric aircraft.

Various energy management tactics have also been researched and used in the research [8]. Three groups of EMSs can be distinguished: RB, OB, and LB EMSs. External energy maximization strategy (EEMS), equivalent consumption minimization strategy (ECMS), state machine control (SMC), classical PI control (CPI), etc., are the traditional methods that were previously used as EMS inside a hybrid power system with renewable sources. Metaheuristic optimization techniques have recently been suggested as a novel way to improve EMS reliability.

A critical literature review is carried out on conventional and metaheuristic algorithms-based EMS and reported in Table 1. Many approaches reported in the literature are hindered by some drawbacks such as high initial state of charge, fall in local optima, etc. Hence, the paper proposes a reliable and simple heuristic COA algorithm to reduce hydrogen consumption by considering all the drawbacks from the literature.

Table 1. Literature on conventional and metaheuristic algorithms-based EMS.

Existing Technologies	EMS Implemented	Execution Mode	Outcomes	Sources/ Application
[9]	ECMS/conventional	Simulation only	Tested using online with low burden and SOC of the battery	FC, B, SC/ FCEV
[10]	Extremum seeking algorithm/conventional	Simulation only	Considered the power, efficiency, and fuel consumption as objectives	FC, B, SC/ FCEV
[11]	Genetic algorithm-based fuzzy EMS	Simulation only	Objectives are minimising H_2 consumption under load variations, a little expert knowledge is required to define the frame of fuzzy rules and an improved GA proposed to automatically determine the fuzzy rules and the parameters of fuzzy MFs	FC_SC HEV
[12]	Rule-based strategy derived from dynamic programming	MATLAB/Simulink	Compared to CDCS, energy efficiency is improved greatly and operating cost is reduced	Range-extended electric vehicles
[13]	Dynamic programming-based online EMS	Simulation only	Power request and SOC are taken as constraints to control the operation for prolongation of all range electric vehicles. For longer driving distances, the energy cost is low compared to the shorter distances of the proposed EMS.	Plug-in HEVs
[14]	Dynamic programming-based EMS	Simulation only	A control strategy is designed for a Chinese urban bus drive cycle according to SOC consumption. The proposed method reduced the computational time with a slight increase in energy consumption compared to the traditional DP strategy.	Range-extended electric bus
[15]	A hybrid optimization method based on adaptive rat swarm optimization and pattern search methods	Simulation and hardware simulation and hardware	Parameter extraction is crucial in PV systems; hence the proposed topologies are used to extract parameters for three PV models. The effectiveness is compared in terms of accuracy and reliability	PV systems
[16]	Modified salp swarm optimization	Simulation and hardware	The modified salp swarm optimization shows the best performance in parameter extraction of solar PV models compared to existing algorithms	Solar PV models
[17]	Golden search optimization algorithm	Simulation only	The proposed algorithm is benchmarked with 23 unimodal, multimodal, and fixed dimensional functions and the results are verified to prove its effectiveness with the well-known gravitational search algorithm (GSA), sine-cosine algorithm (SCA), grey wolf optimization (GWO), and tunicate swarm algorithm (TSA)	To find effective solutions for complex problems
[18]	ECMS, Fl, operational mode, cascade and predictive control/conventional	Simulation and hardware	Fuel utilization is taken as the main objective and compared with 5 control strategies, ECMS shows the best result among all	FC, B, SC/ urban street locomotives
[19]	10 different control strategies/conventional	Simulation only	Hydrogen utilization and life span are taken as objectives, but the execution is not clear	FC, B, SC/ drive cycles
[20]	ECoS/conventional	Simulation only	Hydrogen consumption and SOC are taken as the main objectives, fuel cell utilization is higher compared to battery	FC, B, SC/ four different drive cycles for traction
[21]	Fuzzy logic control strategy/conventional	Simulation only	Within a short time, it covers a long distance compared to FC-B HEV	FC, B, SC/ different drive cycles

Table 1. *Cont.*

Existing Technologies	EMS Implemented	Execution Mode	Outcomes	Sources/ Application
[22]	Decentralized EMS based on a modified droop control	Simulation and hardware	The proposed EMS can split the load power automatically into low- and high-frequency components and allocate them to the FC and SC units, respectively, and the features are high flexibility and durability	FC and SC/ aircraft
[23]	Convex multi-objective optimisation algorithm	Simulation only	The convex multiobjective model aims at minimizing the total fuel consumption during the entire flight mission as well as the corresponding fuel cell size	Hybrid fuel cell power system of more electric aircraft
[24]	Seven metaheuristic algorithms are proposed and compared	Simulation only	The proposed metaheuristic algorithms show their effectiveness in hydrogen consumption with minimum computation time compared to existing EMS algorithms.	FC, B, SC/ aircraft
[25]	SSA/metaheuristic	Simulation only	H_2 utilization is taken as the main objective and compared with the existing one. Attained the least fuel consumption among all	FC, B, SC/ aircraft
[26]	MBA, SSA/metaheuristic	Simulation only	H_2 utilization is taken as the main objective. SSA and MBA are executed in ECMS and EEMS. SSA-EEMS has the lowest fuel consumption among all	FC, B, SC/ aircraft
[27]	SMC, EEMS, FLC, ECMS, CPI/conventional	Simulation and hardware (NI)	H_2 utilization and stress are taken as the main objectives. CPI consumes less H_2 and SMC gained high efficiency among all	FC, B, SC/ aircraft
[28]	Chaos red fox optimization algorithm	Simulation only	The proposed algorithm has the least H_2 consumption (18.19 gms) and is compared with some new metaheuristic algorithms to show its effectiveness.	FC, B, SC/ aircraft
[29]	Particle swarm optimization algorithm	Simulation only	The simulation results are compared with the original ship concerning voltage fluctuations, it is observed that 55% of the reduction is obtained with the proposed methodology	Fuel cell hybrid ship
[30–32]	Mine blast algorithm-based EMS	Simulation only	The proposed MBA technique is tested with EEMS and ECMS to optimise fuel consumption. The MBA ECMS shows the best result compared to existing algorithms.	FC, B, SC/ aircraft
[33]	Salp swarm algorithm-based EMS	Simulation only	The proposed SSA technique is tested with EEMS and ECMS to optimise fuel consumption. The SSA EEMS shows the best result compared to existing algorithms	FC, B, SC/ aircraft

The free lunch theorem [34] states that no existing optimizer can resolve many optimisation issues, hence novel optimizers are still mostly required in the field of EMS research. The coyote optimization algorithm is a brand-new optimizer algorithm that Pierezan et al. [35] proposed (COA). The method effectively optimizes exploration and exploitation, two crucial reinforcement learning ideas, during the optimization phase. Hence, the authors are impressed and implement the COA algorithm for optimal energy management of the energy sources for FC-B-SC HEV. The main contributions of the paper are:

- The COA technique is used to minimize H_2 consumption based on two different energy management strategies. The first one is the ECMS while the second is the EEMS.
- The main purpose of this paper is a validated performance comparison of EMS strategies for an aircraft emergency system based on fuel cells.
- The proposed algorithm is compared with existing conventional and metaheuristic algorithms such as SMC, CPI, ECMS, EEMS, cuckoo search algorithm, GWO, and WOA.

The remainder of the article is arranged as follows: Section 2 presents an overview of existing optimization algorithms and the problem statement. Section 3 presents the proposed COA methodology for EMS. Results and discussion are covered in Section 4. The conclusion of the work is covered in Section 5.

2. Overview of Existing Optimization Algorithms

2.1. External Energy Maximisation Strategy (EEMS)

To enhance the performance of FC-B-SC HEV, it is necessary to optimize the energies from the sources. This task can be accomplished by reducing hydrogen utilisation in the projected system while the SOC of the battery and supercapacitor are kept within the prescribed limits.

The central concept of the external energy maximisation strategy (EEMS) is to reduce hydrogen utilisation by maximising the demand for ESS while meeting its constraints. EEMS is a very simple control strategy, it needs only the cost functions of ESS and does not necessitate the energy calculations of the energy storage elements [27]. Figure 2 shows the general structure of EEMS and ECMS control strategies. The SOC of the battery and voltage of the DC bus are taken as inputs and the change in charge or discharge voltages (ΔV) of the supercapacitor and the reference power of the battery (P_b^{ref}) are taken as outputs for the EEMS control algorithm. The reference power of the fuel cell (P_{fc}^{ref}) is estimated by comparing the powers of the battery and the load through the fuel cell reference current (I_{fc}^{ref}). The charging or discharging state of the supercapacitor is estimated by associating the DC bus voltage with the sum of the reference voltage of the DC bus (V_{dc}^{ref}) and the actual voltage of the supercapacitor.

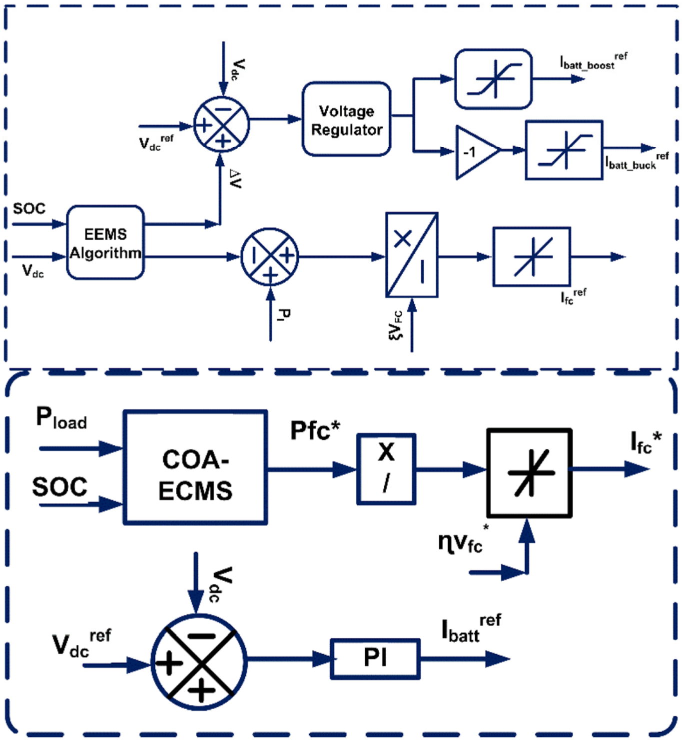


Figure 2. The layout of (**a**) EEMS and (**b**) ECMS [36].

The battery power (P_b) and ΔV are the two variables or objective functions to be estimated for the optimisation in the EEMS technique, i.e., a = [P_b, ΔV]. The energies of the two variables are maximised in a particular time interval and can be formulated as [27]:

$$\text{Maximize } J = -\left(P_b * \Delta T + \frac{1}{2} C_{sc-rated} * \Delta V^2\right) \tag{1}$$

Exposed to

$$P_b * \Delta T \leq \left(SOC - SOC^{min}\right) V_b Q \tag{2}$$

and inequality constraints of Dc bus voltage (V_{dc}) and the P_b are given by:

$$P_b^{Min} \leq P_b \leq P_b^{max} \tag{3}$$

$$V_{dc}^{min} \leq V_{dc} \leq V_{dc}^{max} \tag{4}$$

where P_b represents the power of the battery during the time interval of ΔT, $C_{sc-rated}$ represents the rated capacitance of the supercapacitor, V_b^{min} and V_b^{max} represent the minimum and maximum dc bus voltages, and V_b and Q represent the voltage and capacity of the battery.

The current optimisation algorithm replaces the f_{min} function, which is used by conventional EEMS to improve performance. The output power of the fuel cell, battery, and SOC are taken as decision variables throughout the optimisation process. The minimum and maximum values of variables are taken as: $P_{fc}^{min} = 850$ W, $P_{fc}^{max} = 8800$ W, $P_b^{min} = -1500$ W, $P_b^{max} = 3400$ W, $SOC^{min} = 60$, and $SOC^{max} = 90$. To maximize the objective functions and constraints represented in Equations (1) and (2), the COA algorithm is proposed. The state of charge of the battery and the load power are applied as inputs to the proposed EMS based on the COA algorithm. The outputs P_b^{ref}, ΔV are compared with the voltage of the supercapacitor and load. The difference between the reference and actual voltage of the supercapacitor is applied to the PI controller. The output of the proportional integral controller supplies the battery dc–dc converter with the essential current. Similarly, the variance between load and battery power is converted to the reference fuel cell current.

2.2. State Machine Control Algorithm (SMC)

The basic structure of SMC is shown in Figure 3a. Eight levels could be used to construct the SMC as shown in Figure 3b [27]. Calculating FC power requires an understanding of the battery's SOC as well as the load demand. The FC reference power is indeed the SMC feature's outcome. The FC reference current is then calculated by multiplying the yield of the SMC by both the FC volts as well as the boost converter efficiency. The most significant flaw in the SMC is the requirement for hysteresis control while changing between levels as shown in Figure 3c [27]. The EMS reaction to any changes in load demand is impacted by this problem.

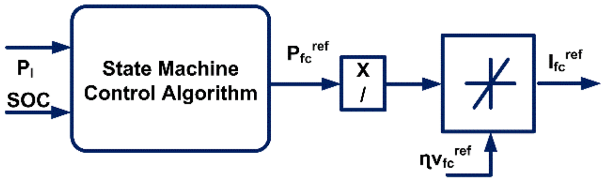
2.3. Classical PI (CPI) Control Strategy

Although PID controllers are frequently employed in industrial and power management applications, PI controllers [37] are also still very common in these fields. This is due to the PI controller's extremely good performance, simple implementation, and readily adjustable parameters on-site (gains). However, employing the derivative (D action) in PID control has some disadvantages, including a quick response to any fluctuations throughout the system's inaccuracy, which would result in an unfavourable fluctuation response. Therefore, using a PI as the controller is favoured in many applications, specifically through noisy situations that lessen the reaction caused by noise. The PI control mechanism is used to acquire the power from the battery and assess the information about its SOC. Within the research, if the battery's SOC is higher than the standard SOC^{ref} value as well as FC's power is reduced, the PI allows the battery to operate with full power. Whenever the battery's SOC is still below the average value, the fuel cell delivers the full load. Equation (14) depicts the transfer function for the PI controller.

$$\frac{P_b}{E} = K_p + \frac{K_i}{S} \tag{5}$$

where E is represented as

$$E = SOC^{ref} - SOC \tag{6}$$

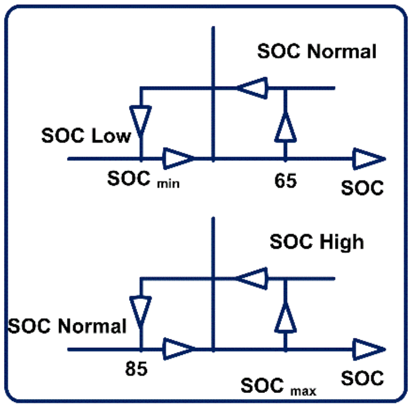


(a)

State	Condition	Output
State=1	If SOC High & $P_l < P_{fc}^{max}$	$P_{fc}^{ref}=P_{fc}^{min}$
State=2	If SOC High & $P_l \epsilon [P_{fc}^{max}, P_{fc}^{min}]$	$P_{fc}^{ref}=P_l$
State=3	If SOC High & $P_l \geq P_{fc}^{max}$	$P_{fc}^{ref}=P_{fc}^{max}$
State=4	If SOC Normal & $P_l < P_{fc}^{opt}$	$P_{fc}^{ref}=P_{fc}^{opt}$
State=5	If SOC Normal & $P_l \epsilon [P_{fc}^{max}, P_{fc}^{opt}]$	$P_{fc}^{ref}=P_l$
State=6	If SOC Normal & $P_l < P_{fc}^{max}$	$P_{fc}^{ref}=P_{fc}^{max}$
State=7	If SOC Low & $P_l < P_{fc}^{max}$	$P_{fc}^{ref}=P_l-P_b^{min}$
State=8	If SOC Low & $P_l \geq P_{fc}^{max}$	$P_{fc}^{ref}=P_{fc}^{max}$

SOC High → SOC > SOC^{max}
SOC Normal → SOC ϵ [85,65]
SOC Low → SOC < SOC^{min}

(b)



(c)

Figure 3. (**a**) Layout of SMC, (**b**) SMC decisions, and (**c**) SMC hysteresis.

2.4. Equivalent Consumption Minimisation Strategy (ECMS)

Several authors [27,38,39] employ the ECMS shown in Figure 2b, a well-instantaneous cost-function global optimization technique. The objective is to reduce the amount of fuel used by the fuel cell and the equal amount of fuel needed to maintain the battery's SOC. The strategy outlined in [38] has been employed in the present study, which controls the battery SOC using the energy penalty factor. This is how the optimization problem is defined.

Find the best response $x = P_{fc}, \propto, P_b$, which minimizes

$$F = \left[P_{fc} + \propto P_b\right] * \Delta T \tag{7}$$

Under the equality constraints

$$P_l = P_{fc} + P_b \tag{8}$$

$$\propto = 1 - 2\mu \frac{\left(SOC - 0.5\left(SOC^{max} + SOC^{\min}\right)\right)}{SOC^{max} + SOC^{min}} \tag{9}$$

While the following descriptions are provided for the decision variable bounds

$$P_{fc}^{max} \leq P_{fc} \leq P_{fc}^{min} \tag{10}$$

$$P_{b}^{max} \leq P_{b} \leq P_{b}^{min} \tag{11}$$

$$0 \leq \propto \leq 100 \tag{12}$$

where P_{fc}^{min}, P_{fc}^{max}, and P_{fc} are the fuel cell minimum, maximum, and actual powers, $\propto$ is the penalty coefficient, and μ is a balancing constant of SOC.

The dc-link voltage is usually regulated by battery converters. Therefore, the supercapacitor power is not taken into account throughout the optimization process. In other words, the supercapacitors are replenished with almost the same energy as from the battery system as soon as they drain. As a result, during a certain loading condition, the FC and battery seem to be the only ones to contribute the full load energy. MPPT and ECMS algorithms are hybridized for energy management to improve the motion range of mobile welding robots [40].

2.5. Grey Wolf Optimisation Algorithm (GWO)

The GWO algorithm is primarily determined by the motivation of the attributes and hunting strategy of the grey wolf (GW). It is a trustworthy and efficient meta-heuristic technique. The predatory animals at the highest levels of the food chain include GWs. Although wolves like to congregate in packs, a relatively tight society with alpha (Xα), beta (Xβ), and delta (Xδ) masters as first, second, and third best solutions are visible. The hunting interaction of the GW group includes tracking, chasing, and approaching the target. The food source is then pursued, circled, and harassed till it settles down, at which point it is attacked.

The GWO algorithm wildlife process and the associated social structure are replicated in the flowchart, as seen in Figure 4a.

2.6. Cuckoo Search Algorithm

The cuckoo search algorithm is an exploring method that draws inspiration from the behaviour of obligatory brood parasites inside the tribe of cuckoo birds. These birds typically deposit their eggs within the nests of any other bird species and disrupt neighbouring eggs to make sure that their eggs develop in these foreign nests. However, when the hosting bird sees the alien egg, they immediately throw the alien fragrance away or abandoned the nest. A cuckoo's chances of thriving in such a colony are therefore improved by emulating the parental bird's behaviour. Consequently, a variety of engineering challenges including optimization tasks have been solved using the unique cuckoo search algorithm optimization approach depicted in Figure 4b.

2.7. Whale Optimisation Algorithm (WOA)

The WOA meta-heuristic optimization technique was inspired by the behaviour of whale sharks. These whales engage in a unique feeding behaviour known as bubble-net feeding, whereby they create droplets by circling or by travelling along a nine-shaped track. The behaviour of whales is mainly divided into two parts, which are searching and encircling prey and updating position spirally. By modelling the two phases mathematically, an optimal value can be reached. The whale bubble-net feeding-associated optimization flowchart is shown in Figure 5.

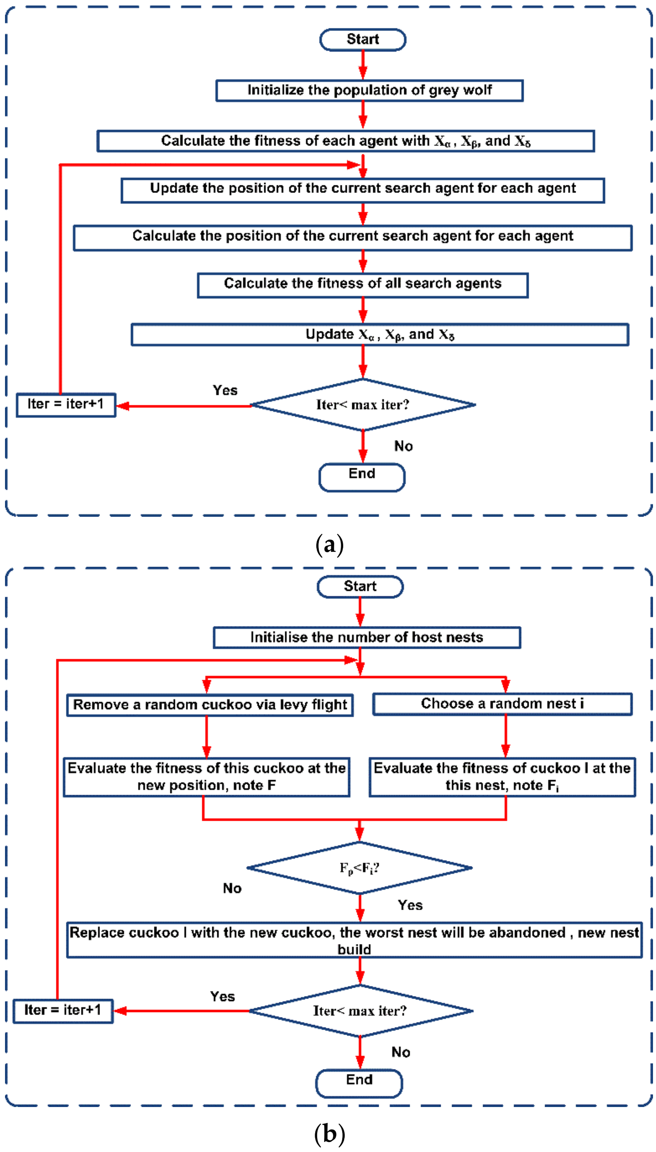


Figure 4. Basic flowchart of (**a**) GWO algorithm and (**b**) cuckoo search algorithm.

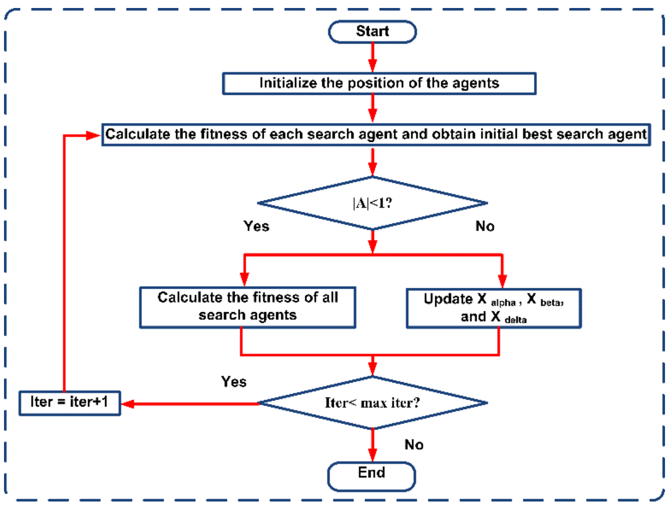


Figure 5. Basic flowchart of WOA algorithm.

3. Proposed COA Algorithm

The coyote optimization algorithm (COA) was first presented by Pierezan et al., in 2018 [35]. The North American Canis latrans species was used as the model for this metaheuristic algorithm. The COA has particular expertise in affecting coyotes' family structure and environmental acclimatisation. The main advantage of the COA technique is that it maintains the equilibrium between the exploration and exploitation phases of the best solution. Unlike GWO, COA is unconcerned with the hegemonic and hierarchical concepts that these creatures uphold. Additionally, it depends on the social organization and activities of the coyotes as well as the carnivores that are hunted in GWO. Animals have cooperative traits as they move toward the prey as a group even though each animal has a personal urge to ingest it. Coyotes have a good sense of smell that helps them find their prey. During the foraging period, coyotes attack their target in groups, forcing the hunters to relocate to safer areas. When coyotes attack their prey, they are adequately protected from threat and travel abnormally haphazardly away from their current location.

This process begins with implementing the birth rate of coyotes. The social state, state of charge, of the Cth coyote in the Pth pack, can be initialized in the following ways:

$$SOC_{C,j}^{P,t} = l_j + r_j * (u_j - l_j) \quad (13)$$

where r_j is a random variable between [0, 1], and l_j and u_j are the minimum and maximum bounds of the parameters to be constructed. A fitness function that may be computed as follows is used to describe the coyotes' adaptability to the current social conditions:

$$fit_C^{p,t} = f_C^{P,t}\left(SOC_C^{P,t}\right) \quad (14)$$

The coyotes are utilized to divide into packs at the start of the procedure; they have a chance to quit their groups with a probability of,

$$P_e = 0.005.N_C^2 \quad (15)$$

The procedure of moving coyotes across packs aids in promoting the ethnicities of the populations by boosting relationships. Out of the three alphas in COA, one is chosen and is presented as follows:

$$alp^{P,t} = \left\{SOC_C^{P,t} \middle| arg_{C=\{1,2,\ldots,N\}} minf\left(SOC_C^{P,t}\right)\right\} \quad (16)$$

It is presumed in COA that all coyotes are sufficiently organized to embrace the same social culture. As a result, the data from the coyotes are connected and calculated as just a cultural propensity as follows:

$$Culture_j^{P,t} = \begin{cases} O_{\frac{(N_C+1)}{2},j}^{P,t} & N_{c\ is\ odd} \\ \frac{O_{\frac{N_c}{2},j}^{P,t} + O_{(\frac{N_C}{2}+1),j}^{P,t}}{2} & otherwise \end{cases} \quad (17)$$

where $O^{P,t}$ denotes the coyote population's organized social structure at the tth specific moment in time through park, P. The creation of a young one will be depicted by integrating the social circumstances of two randomly chosen parents while considering the influence of the environment. The ages of coyotes, age $C^{P,t}$, are calculated in COA as follows:

$$pup_j^{P,t} = \begin{cases} SOC_{r1,j}^{P,t} & rnd_j < P_{sc}\ or\ j = j_1 \\ SOC_{r2,j}^{P,t} & rnd_j < P_{sc} + P_{ac}\ or\ j = j_2 \\ R_j & Otherwise \end{cases} \quad (18)$$

where the social conditions of $r1$ and $r2$ at time t are indicated by $SOC_{r1,j}^{P,t}$ and $SOC_{r2,j}^{P,t}$ in the Pth pack, the two extents of the problem are labelled as j_1 and j_2, R_j indicates the random number in the prescribed bounds and lastly, P_{sc} and P_{ac} indicate the probability of scattering and association calculated as follows:

$$P_{sc} = \frac{1}{D} \tag{19}$$

$$P_{ac} = \frac{(1 - P_{sc})}{D} \tag{20}$$

Two variables were supplied in COA for modelling these rules, namely, the solution groups indicating the worst fitness value (ω), as well as the number of coyotes in these groups (φ). Where D is indeed the task dimension, within the group, various rules regulate the operations of such coyotes' birth and death.

The regulating guidelines [41] for this procedure are shown in Figure 6a. By assuming that the coyotes were subject to the alpha impact ($\delta 1$) and group effect ($\delta 2$), this may be recalculated as:

$$\delta_1 = alp^{P,t} - SOC_{C_{r1}}^{P,t} \tag{21}$$

$$\delta_2 = Cult^{P,t} - SOC_{C_{r2}}^{P,t} \tag{22}$$

where C_{r1} and C_{r2} indicate random coyotes. Depending upon the influences of such alpha and pack, the coyote's equilibrium point is changed as follows:

$$SOC_C^{P,t,new} = SOC_C^{P,t,old} + r_1 * \delta_1 + r_2 * \delta_2 \tag{23}$$

Algorithm:1 Birth and death inside a pack.

- Compute ω and φ
- If φ = 1 then
- The pup survives and the only coyote in ω dies.
- elseif φ > 1 then
- The pup survives and the oldest coyote in ω dies.
- else
- The pup dies.
- end if

(a)

Algorithm:2 Pseudo code of the COA.

- Initialize N_p packs with N_c coyotes each (Eq.13)
- Verify the Coyote's adaptation (Eq.14)
- While stopping criterion is not achieved do
- for each p Pack do
- Define the alpha coyote of the pack (Eq.16)
- Compute the social tendency of the pack (Eq.17)
- for each c coyotes the p pack do
- Update the social condition (Eq.22)
- Evaluate the new social condition (Eq.23)
- Adaptation (Eq.24)
- end for
- Birth and death (Eq.18)
- end for
- Transition between packs (Eq.15)
- Update the coyote's ages
- end while
- Select the best adapted coyote.

(b)

Methodology incorporated Coyotes optimisation Algorithm

- Initialize the data
- Load the input data of Fuel cell, Battery, Super capacitor and Load.
- Initialize a population dimension of N_p * dim represents probable solutions (P_{bat} * ΔV)
- for each p Pack do
- perform the pseudo code given in (b)
- Observe the Hydrogen consumption $H_{2.cons}$ of the pack
- perform the iterations and find the best hybdrogen consumption of the pack
- Update the new hydrogen consumption
- end while
- Select the best Hydrogen Consumtion (gms).

(c)

Figure 6. (**a**) Birth and death inside a pack of COA algorithm, (**b**) pseudo code of COA algorithm, and (**c**) suggested approach integrated COA algorithm.

The following conditions must be met to update the social situation:

$$SOC_C^{P,t+1} = \begin{cases} SOC_C^{P,t,new} & fit_C^{P,t,new} < fit_C^{P,t} \\ SOC_C^{P,t} & otherwise \end{cases} \tag{24}$$

The flowchart [42] in Figure 6b summarises the processes taken in the COA process. In Figure 6c, the suggested methodology [36] for the solution that included a modified COA is displayed. A populated matrix of dimension Np* dim, that includes possible responses for Pb and ΔV, is initialized at the beginning. A potential response to the issue is represented by each row of the populated matrix. The COA processes listed in Figure 6b are carried out for each row while paying attention to the utilisation of hydrogen for every group. The pack that uses the least hydrogen is considered the most suitable response.

4. Results and Discussion

The simulation design of the system under this work consists of a hybrid power source with an FC and ESS, and the structure is implemented to supply an aircraft load as shown in Figure 1.

The load profile of the aircraft is shown in Figure 7. The scheme module's specifications are displayed in Table 2. The battery is discharged, and the reference current from the battery is supplied to the two dc–dc converters to create the battery reference voltage and DC voltage. The boost converter receives the reference fuel cell current to maximize its performance. The COA-based EMS is designed to reduce fuel utilization while delivering the aircraft's load demand. The COA algorithm is used in two different EMSs: (1) COA-based EEMS and (2) COA-based ECMS. The COA block receives the P_{load} profile and battery SOC before producing the I_{fc}^{ref} and I_b^{ref}. The planned COA's main goal is to reduce hydrogen use. A comparative analysis with various optimization algorithms is conducted to verify the validity of the suggested method. An essential supply for the aircraft's demand is provided by the blended fuel cell, battery, and supercapacitor. Initially, the demand is provided by a three-phase supply; during that time, the fuel cell is utilised for recharge till it achieves a rated power. The hybrid system is used to provide all necessary demands if the main source is disrupted. The battery provides power to adjust the Dc link voltage to that reference value when the SC is drained and its voltage level drops below the required voltage. In this case, the fuel cell provides all of the power needed to load and replenish the supercapacitor. Whenever the fuel cell achieves its peak power, the battery is used to supplement the power till it exceeds the threshold output, at which point the supercapacitor splits the demand.

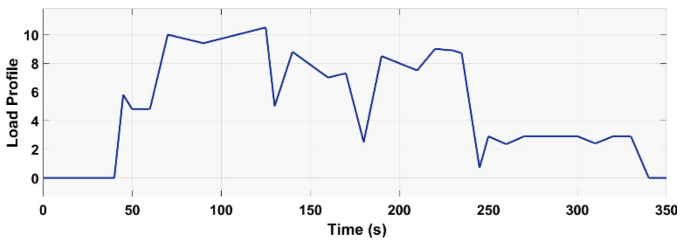


Figure 7. Emergency landing cycle recorded by Bombardier Aerospace.

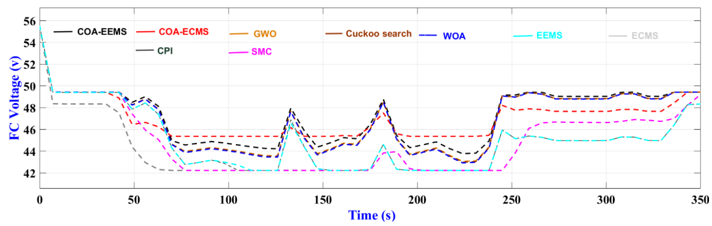
The results supported the suggested COA's efficiency because it consumes the least amount of hydrogen when referring to the existing algorithms. The comparative analysis of FC voltage, current, and hydrogen consumption of the proposed algorithms is shown in Figure 8a–c. The simulation result analysis of battery voltage, current, and state of charge for the proposed algorithms are shown in Figure 9a–c. Figure 10a,b displays the simulation result analysis of SC voltage and current for the proposed algorithms. In contrast to the load profile, Figure 11a,b also displays the changes in hybrid energy sources over time. The response indicated that the fuel cell serves as the main emergency reserve, with the battery and supercapacitor serving as secondary sources used to carry additional load throughout the scenario that FC draws its maximum possible power. The battery's SOC is roughly equivalent to 65% at the start of the test shown in Figure 9c; however, while FC is being used to charge the battery at this time, the SOC increases. After t = 40 s, the primary source is cut off, and the hybrid system is employed to deliver the load. As a result, the battery SOC starts to decline and continues to until the simulation is complete.

Table 2. Specifications of fuel cell, battery, and supercapacitor in Simulink Mode.

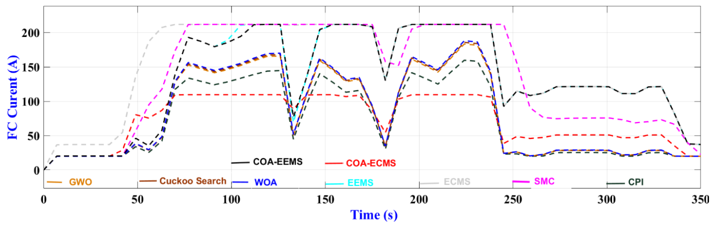
Sl. No		Specifications	
1	Fuel Cell	Rated Voltage (V)	41.15
		Rated Current (A)	250
		Number of Cells	65
		Efficiency (%)	50
		Operating Temp. (°C)	45
		Air flowrate (Ipm)	732
		Fuel Pressure (bar)	1.16
		Air Pressure (bar)	1
2	Battery	Rated Voltage (V)	48
		Capacity (Ah)	40
		Max. Capacity (Ah)	40
		Full Charge Voltage	55.88
		Rated discharge Current (A)	17.4
		Internal resistance	0.012
3	Supercapacitor	Rated Capacitance (F)	15.6
		Series Resistance (Ω)	0.15
		Rated Voltage (V)	291.6
		Surge Voltage (V)	307
		No. of Capacitors in Series	108
		No. of Capacitors in Parallel	1
		Number of Layers	6
4	Protective Resistor		15 KW
5	Boost Converter		4 KW
6	Buck Converter		1.2 KW
7	Inverter	15 KVA, 240/220 V and 400 Hz	

The suggested COA algorithms have been used to achieve the minimum SOC, which validates that the battery seems to be more dependable for supporting the load than the FCs, leading to minimum hydrogen consumption utilization. This also confirms that the suggested approaches are preferred in terms of decreasing the quantity of hydrogen consumption when contrasted to the existing technologies. The proposed algorithms are tested using Opal-RT 5700 real-time simulator shown in Figure 12.

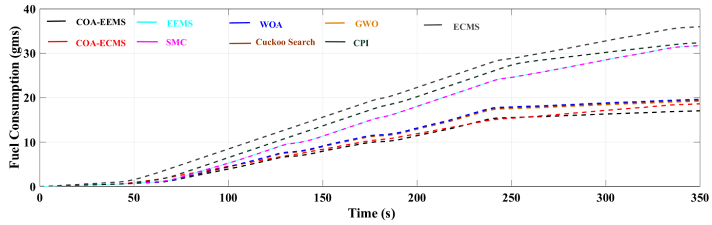
The voltage level of the real-time simulator is limited to −16 V to +16 V. Hence, while executing the proposed algorithm a gain factor of 0.5 is taken to reduce the magnitude of fuel consumption to the measured level of the real-time simulator. The per division magnitude of the oscilloscope connected to the output terminals of the Opal-RT 5700 real-time simulator controller board is taken as 1.6 A which represents 1.6 gms of fuel consumption. Figure 13a–e shows the HIL results of fuel consumption by (a) the WOA algorithm, (b) the cuckoo search algorithm, (c) the GWO algorithm, (d) the COA-ECMS algorithm, and (e) the COA-EEMS algorithm.



(**a**)

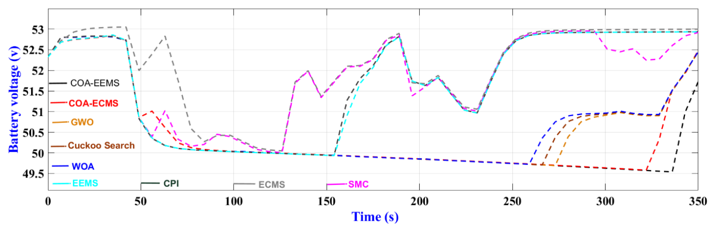


(**b**)

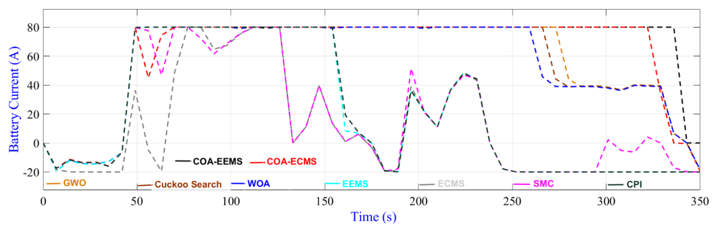


(**c**)

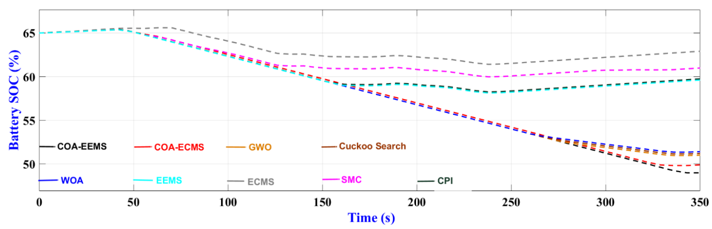
Figure 8. Comparative analysis of proposed algorithm with others: (**a**) FC voltage (V), (**b**) FC current (A), and (**c**) FC fuel consumption (gm).



(**a**)

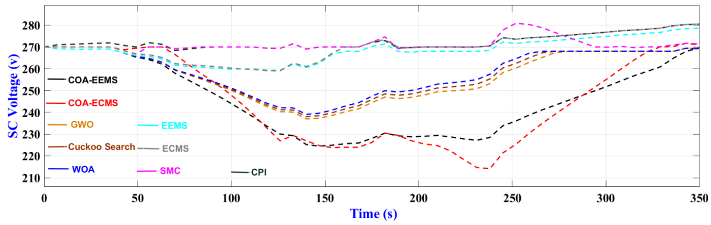


(**b**)

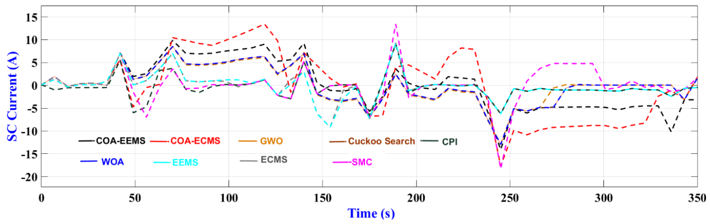


(**c**)

Figure 9. Comparative analysis of proposed algorithm with others for (**a**) battery voltage (V), (**b**) battery current (A), and (**c**) battery SOC (%).

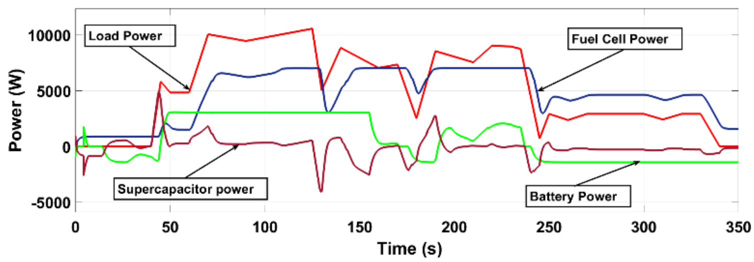


(**a**)

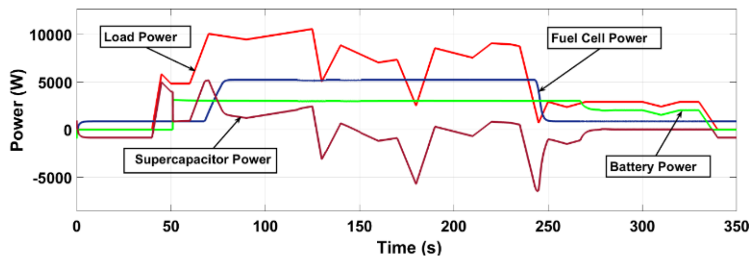


(**b**)

Figure 10. (**a**,**b**) Displays the comparative analysis of SC voltage and current of the proposed algorithms.



(**a**)



(**b**)

Figure 11. Simulation result of (**a**) power shared from sources to meet load demand by the COA-ECMS algorithm and (**b**) power shared from sources to meet load demand by COA-EEMS algorithm.

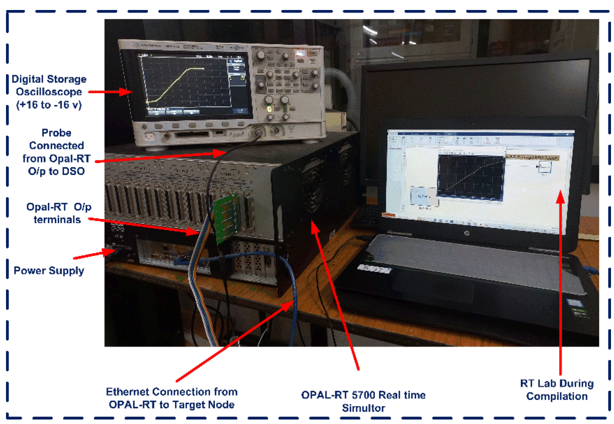
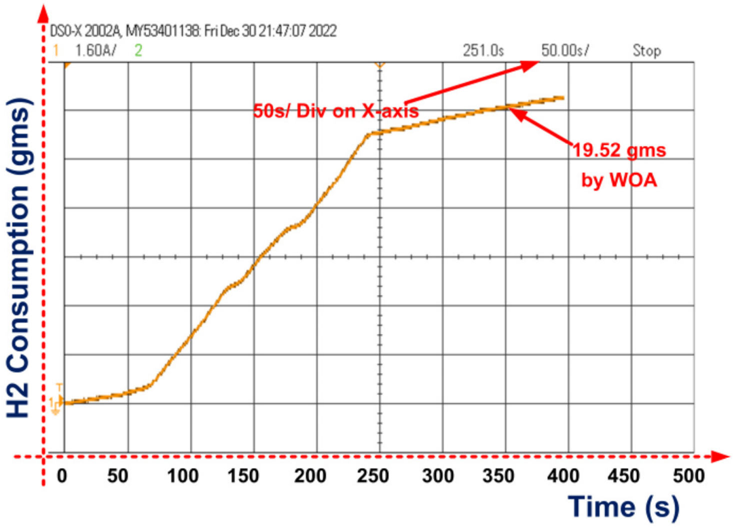
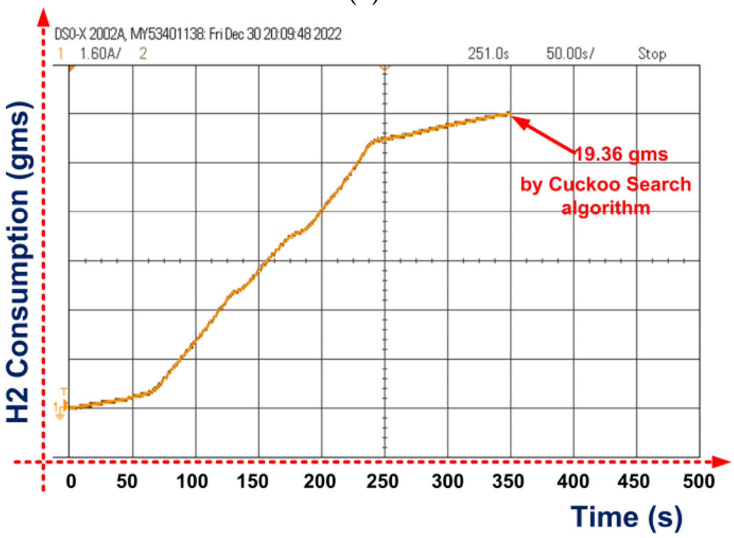


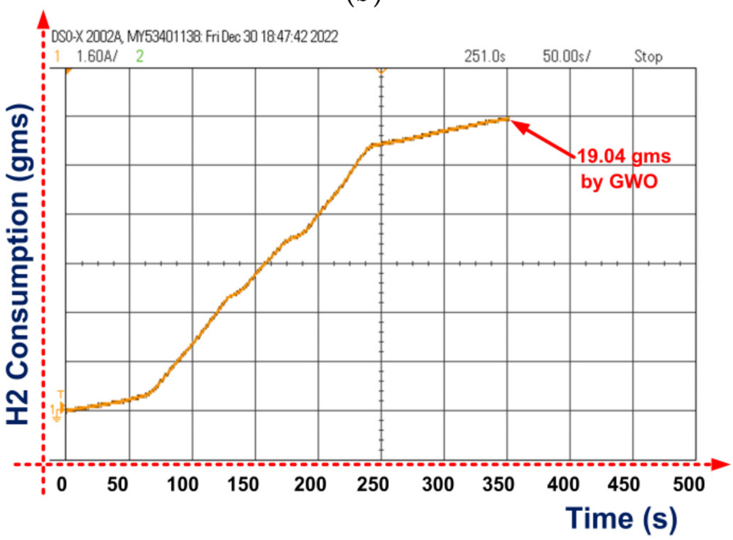
Figure 12. Real-time HIL simulator test bench.



(**a**)

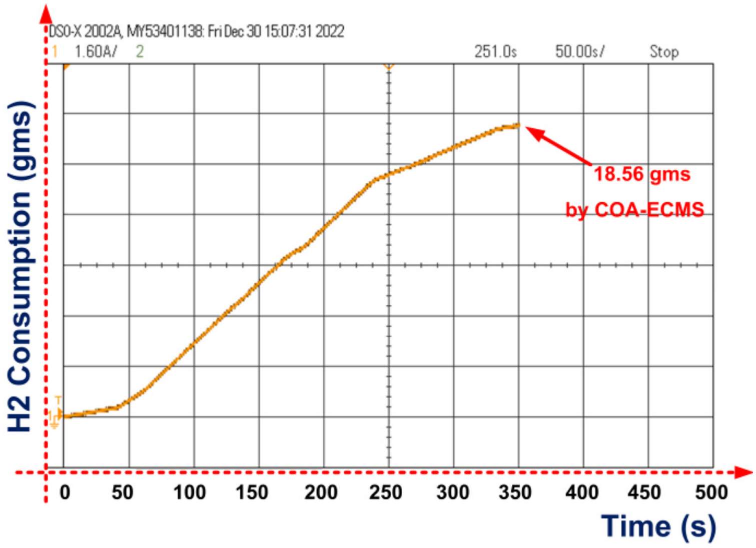


(**b**)

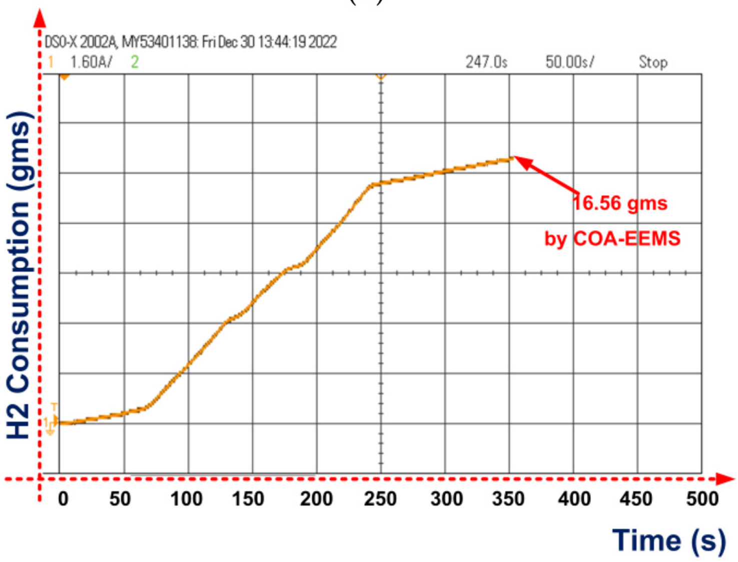


(**c**)

Figure 13. *Cont*.



(**d**)



(**e**)

Figure 13. Opal-RT result of fuel consumption by (**a**) WOA algorithm, (**b**) cuckoo search algorithm, (**c**) GWO algorithm, (**d**) COA-ECMS algorithm, and (**e**) COA-EEMS algorithm.

The complete analysis of the proposed EMS is presented in Table 3. Moreover, the analyses of hydrogen consumption and efficiency are carried out for all the existing and proposed COA methodologies and reported in Tables 4 and 5. A comparative analysis between the simulation and HIL results is reported in Table 6.

Table 3. Complete analysis of proposed EMSs.

Parameter / Algorithm	V_{fc} (V)	I_{fc} (A)	H_{con} (gm)	V_b (V)	I_b (A)	SOC_b (%)	V_{sc} (V)	I_{sc} (A)
CPI	42–55.5	0–200	31.7	50–53.2	0–80	58–66	268–280	−7–10
SMC	42–55.5	0–200	31	50.2–52.8	0–80	60–66	266–280	−17.5–14
ECMS	42–55.5	0–200	35.8	50.2–53.1	0–80	62.5–67	260–280	−12.5–8
EEMS	42–55.5	0–200	31.8	50–53	0–80	57.5–66	260–280	−9–9

Table 3. *Cont.*

Parameter	V_{fc} (V)	I_{fc} (A)	H_{con} (gm)	V_b (V)	I_b (A)	SOC_b (%)	V_{sc} (V)	I_{sc} (A)
Algorithm								
WOA	43–55.5	0–190	19.6	49.9–52.5	0–80	52–66	240–270	−7–10
Cuckoo search algorithm	43–55.5	0–185	19.4	49.8–52.5	0–80	51.5–66	238–270	−7–10
GWO	43–55.5	0–180	19.2	49.7–52.5	0–80	51–66	236–270	−7–10
COA-ECMS	45.5–55.5	0–120	18.6	49.6–52.5	0–80	50–66	225–270	−17.5–14
COA-EEMS	45–55.5	0–160	16.9	49.5–52.5	0–80	48–66	215–270	−10–10

Table 4. Comparative analysis with existing technologies by hydrogen consumption (gm).

H_2 Consumption (gms)	(26)	(36)	(40)	Proposed Methodologies (gms)	Proposed Methodologies (Watthour)
Algorithms					
CPI	31.63		--	31.7	0.0369
SMC	32.063		--	31	0.0360
ECMS	35.97		--	35.8	0.0416
EEMS	31.677	31.674	--	31.8	0.0370
WOA	--		--	19.6	0.0228
Cuckoo search algorithm	--		--	19.4	0.0226
GWO	--	19.40	19.40	19.2	0.0223
COA-ECMS	--		--	18.6	0.0216
COA-EEMS	--	19.3778		16.9	0.0197

Table 5. Comparative analysis with existing technologies by efficiency (%).

Efficiency (%)	(26)	(36)	(40)	Proposed Methodologies
Algorithm				
CPI	73.771		--	73.12
SMC	78.521		--	77.95
ECMS	72.512		--	71.9
EEMS	74.149	74.15	--	74.1
WOA	--		--	82.2
Cuckoo search algorithm	--		--	82.84
GWO	--	68.27	78.3	83.51
COA-ECMS	--		--	87.629
COA-EEMS	--	82.09	82	90.17

Table 6. Comparative analysis between simulation and Opal-RT real-time HIL simulator.

Proposed Algorithms	Fuel Consumption (gms)/Simulation	Fuel Consumption (gms)/Opal-RT Real-Time HIL Simulator
WOA	19.6	19.52
Cuckoo search algorithm	19.4	19.36
GWO	19.2	19.04
COA-ECMS	18.6	18.56
COA-EEMS	16.9	16.96

Figure 14 shows the pictorial representation of the overall performance of the proposed EMS. The suggested COA-EEMS and ECMS yield a minimum hydrogen consumption utilization of 16.9 gm and 18.6 gm, whereas the ECMS yields a maximum hydrogen utilization of 35.8 gm. The efficiency is calculated from the equation below:

$$\eta = \frac{P_l}{P_{fc-in} + P_{b-in} + P_{sc-in}} \tag{25}$$

where P_{fc-in} and P_{b-in} are the fuel and battery powers that are connected as inputs to the DC–DC converters, and P_{sc-in} indicates supercapacitor power. The COA-EEMS method was successful in achieving an efficiency of 90.17%, while COA-ECMS only managed to achieve a productivity of 87.629%.

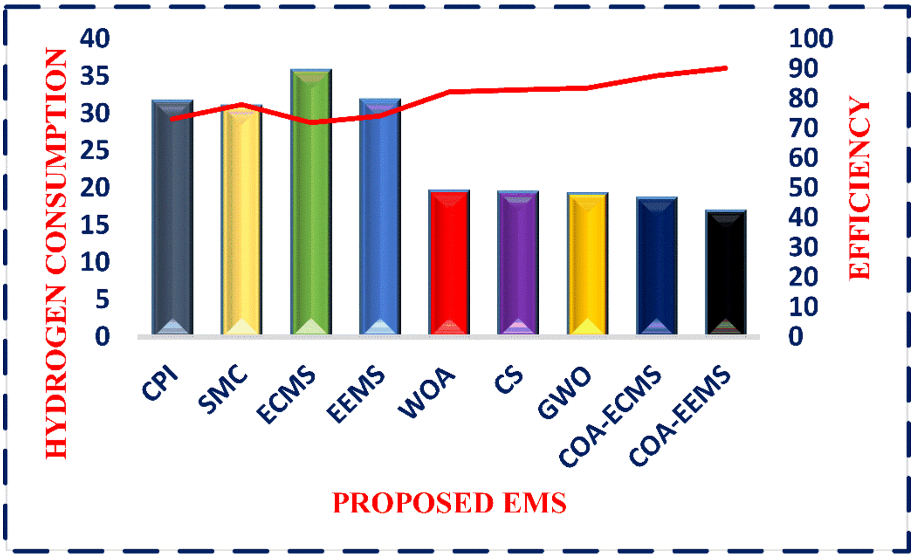


Figure 14. Comparative analysis of proposed EMS.

Lastly, one could conclude that the results obtained proved the uniqueness and effectiveness of the suggested COA-EEMS in resolving the issue of hydrogen utilization to provide aircraft load demand in emergency scenarios.

5. Conclusions

This research study suggests an optimal energy management strategy (EMS) for a fuel cell hybrid electric aircraft based on a modified coyote optimization algorithm (COA). A fuel cell (FC) and ESS make up such a technology. The main objective of the proposed EMS is to minimize hydrogen utilization. The proposed COA-ECMS verifies its robustness in minimizing hydrogen utilization against the existing approaches and the COA-EEMS algorithm attained the best results compared to COA-ECMS. An evaluation of COA's efficiency and reliability is performed in contrast to existing approaches. CPI, SMC, ECMS, EEMS, GWO, cuckoo search algorithm, and WOA are some of these methods. The Opal-RT real-time HIL results verified the suggested COA's advantages. Compared to the ECMS approach, the suggested COA-ECMS algorithm minimizes hydrogen fuel consumption by 51.8% and the COA-EEMS algorithm minimizes hydrogen fuel utilisation by 47%. The approaches are evaluated from worst to best according the least hydrogen utilisation as follows: ECMS, EEMS, CPI, SMCS, GWO, cuckoo search algorithm, WOA, COA-ECMS, and COA-EEMS. Further, the proposed algorithms are testing for different FC-HEVs to minimise fuel consumption, improve the life span of ESS, and reduce the stresses on the devices.

Author Contributions: R.V.: conceptualization, methodology, simulation, validation, writing draft, visualization; D.C.: conceptualization, methodology, validation, draft-review and editing, visualization, and supervision. All authors have read and agreed to the published version of the manuscript.

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References

1. Hassan, F. Fuel cell hybrid electric vehicle (FCHEV): Novel fuel cell/SC hybrid power generation system. *Energy Convers. Manag.* **2018**, *156*, 192–201.
2. Ahmed, F.; Rezk, H. Multi-verse optimizer for identifying the optimal parameters of PEMFC model. *Energy* **2018**, *143*, 634–644.
3. Sulaiman, N.; Hannan, M.A.; Mohamed, A.; Ker, P.J.; Majlan, E.H.; Wan Daud, W.R. Optimization of energy management system for fuel-cell hybrid electric vehicles: Issues and recommendations. *Appl. Energy* **2018**, *228*, 2061–2079. [CrossRef]
4. Phatiphat, T.; Rael, S. The benefits of hybridization. *IEEE Ind. Electron. Mag.* **2009**, *3*, 25–37.
5. Gwénaëlle, R.-V.; Saballus, M.; Schmithals, G.; Schirmer, J.; Kallo, J.; Friedrich, K.A. Improving the environmental impact of civil aircraft by fuel cell technology: Concepts and technological progress. *Energy Environ. Sci.* **2010**, *3*, 1458–1468.
6. Gwenaelle, M.R.-V.; Kallo, J.; Friedrich, A.K.; Schirmer, J.; Saballus, M.; Schmithals, G. Fuel cells for aircraft applications. *ECS Trans.* **2011**, *30*, 271.
7. Xavier, R.; Sareni, B.; De Andrade, A. More electricity in the air: Toward optimized electrical networks embedded in more-electrical aircraft. *IEEE Ind. Electron. Mag.* **2012**, *6*, 6–17.
8. Venkatasatish, R.; Dhanamjayulu, C. Reinforcement learning based energy management systems and hydrogen refuelling stations for fuel cell electric vehicles: An overview. *Int. J. Hydrogen Energy* **2022**, *47*, 27646–27670. [CrossRef]
9. Simona, O.; Serrao, L.; Rizzoni, G. Adaptive equivalent consumption minimization strategy for hybrid electric vehicles. In Proceedings of the Dynamic Systems and Control Conference, Cambridge, MA, USA, 12–15 September 2010; Volume 44175, pp. 499–505.
10. Nicu, B. Real-time optimization strategy for fuel cell hybrid power sources with load-following control of the fuel or air flow. *Energy Convers. Manag.* **2018**, *157*, 13–27.
11. Ridong, Z.; Tao, J. GA-based fuzzy energy management system for FC/SC-powered HEV considering H_2 consumption and load variation. *IEEE Trans. Fuzzy Syst.* **2017**, *26*, 1833–1843.
12. Jiuyu, D.; Chen, J.; Gao, M.; Wang, J. Energy efficiency-oriented design method of power management strategy for range-extended electric vehicles. *Math. Probl. Eng.* **2016**, *2016*, 9203081.
13. Zeyu, C.; Liu, W.; Yang, Y.; Chen, W. Online energy management of plug-in hybrid electric vehicles for prolongation of all-electric range based on dynamic programming. *Math. Probl. Eng.* **2015**, *2015*, 368769.
14. Xiaogang, W.; Chen, J.; Hu, C. Dynamic programming-based energy management system for range-extended electric bus. *Math. Probl. Eng.* **2015**, *2015*, 624649.
15. Mahdiyeh, E.; Akbari, E.; Sadr, S.T.S.; Ibrahim, B.F. A novel hybrid algorithm based on rat swarm optimization and pattern search for parameter extraction of solar photovoltaic models. *Energy Sci. Eng.* **2022**, *10*, 2689–2713.
16. Mokhtar, Y.; Eslami, M.; Noroozi, M.; Mohammadi, H.; Kamari, O.; Palani, S. Modified Salp Swarm Optimization for Parameter Estimation of Solar PV Models. *IEEE Access* **2022**, *10*, 110181–110194.
17. Mohammad, N.; Mohammadi, H.; Efatinasab, E.; Lashgari, A.; Eslami, M.; Khan, B. Golden search optimization algorithm. *IEEE Access* **2022**, *10*, 37515–37532.
18. Stéphane, C.; Gaoua, Y.; Lopez, P. A combinatorial optimisation approach to energy management strategy for a hybrid fuel cell vehicle. *Energy* **2017**, *133*, 219–230.
19. Daming, Z.; Ravey, A.; Al-Durra, A.; Gao, F. A comparative study of extremum seeking methods applied to online energy management strategy of fuel cell hybrid electric vehicles. *Energy Convers. Manag.* **2017**, *151*, 778–790.
20. Mauro, G.C.; Costa-Castelló, R.; Roda, V.; Nigro, N.M.; Junco, S.; Feroldi, D. Energy management strategy for fuel cell-supercapacitor hybrid vehicles based on prediction of energy demand. *J. Power Sources* **2017**, *360*, 419–433.
21. Aymen, F.; Mahmoudi, C. Design and analysis of a novel power management approach, applied on a connected vehicle as V2V, V2B/I, and V2N. *Int. J. Energy Res.* **2019**, *43*, 6869–6889.
22. Jiawei, C.; Song, Q. A decentralized energy management strategy for a fuel cell/supercapacitor-based auxiliary power unit of a more electric aircraft. *IEEE Trans. Ind. Electron.* **2018**, *66*, 5736–5747.
23. Mohammad, J.S.; Zarenia, O.; Rostami, S.M.H.; Wang, J.; Lim, S. Convex multi-objective optimization for a hybrid fuel cell power system of more electric aircraft. *Int. Trans. Electr. Energy Syst.* **2020**, *30*, e12427.
24. Hasan, Ç.; Kandemir, I. Active energy management based on meta-heuristic algorithms of fuel cell/battery/supercapacitor energy storage system for aircraft. *Aerospace* **2021**, *8*, 85.

25. Ahmed, F.; Rezk, H.; Nassef, A.M. Robust hydrogen-consumption-minimization strategy based salp swarm algorithm for energy management of fuel cell/supercapacitor/batteries in highly fluctuated load condition. *Renew. Energy* **2019**, *139*, 147–160.
26. Hegazy, R.; Nassef, A.M.; Abdelkareem, M.A.; Alami, A.H.; Fathy, A. Comparison among various energy management strategies for reducing hydrogen consumption in a hybrid fuel cell/supercapacitor/battery system. *Int. J. Hydrogen Energy* **2021**, *46*, 6110–6126.
27. Njoya, M.S.; Dessaint, L.-A.; Al-Haddad, K. A comparative study of energy management schemes for a fuel-cell hybrid emergency power system of more-electric aircraft. *IEEE Trans. Ind. Electron.* **2013**, *61*, 1320–1334. [CrossRef]
28. Zhirun, H.; Liu, S.; Ebrahimian, H. Aircraft energy management system using chaos red fox optimization algorithm. *J. Electr. Eng. Technol.* **2022**, *17*, 179–195.
29. Xin, P.; Chen, H.; Guan, C. Energy Management Optimization of Fuel Cell Hybrid Ship Based on Particle Swarm Optimization Algorithm. *Energies* **2023**, *16*, 1373.
30. Ali, S.; Bahreininejad, A.; Eskandar, H.; Hamdi, M. Mine blast algorithm: A new population-based algorithm for solving constrained engineering optimization problems. *Appl. Soft Comput.* **2013**, *13*, 2592–2612.
31. Mohammed, A.; Alkhalaileh, S.; Albashish, D.; Mafarja, M.; Bsoul, Q.; Dorgham, O. A hybrid mine blast algorithm for feature selection problems. *Soft Comput.* **2021**, *25*, 517–534.
32. Jianzhou, Z.; Ramadan, H.S.; Becherif, M. Metaheuristic-based energy management strategies for fuel cell emergency power unit in electrical aircraft. *Int. J. Hydrogen Energy* **2019**, *44*, 2390–2406.
33. Seyedali, M.; Gandomi, A.H.; Mirjalili, S.Z.; Saremi, S.; Faris, H.; Mirjalili, S.M. Salp Swarm Algorithm: A bio-inspired optimizer for engineering design problems. *Adv. Eng. Softw.* **2017**, *114*, 163–191.
34. David, H.W.; Macready, W.G. No free lunch theorems for optimization. *IEEE Trans. Evol. Comput.* **1997**, *1*, 67–82.
35. Juliano, P.; Coelho, L.D.S. Coyote optimization algorithm: A new metaheuristic for global optimization problems. In Proceedings of the 2018 IEEE Congress on Evolutionary Computation (CEC), Rio de Janeiro, Brazil, 8–13 July 2018; IEEE: Piscataway, NJ, USA; pp. 1–8.
36. Ahmed, F.; Al-Dhaifallah, M.; Rezk, H. Recent coyote algorithm-based energy management strategy for enhancing fuel economy of hybrid FC/Battery/SC system. *IEEE Access* **2019**, *7*, 179409–179419.
37. Hao, Y.; Dai, H.; Wu, W.; Xie, J.; Shen, J.; Wei, X. A fuzzy logic PI control with feedforward compensation for hydrogen pressure in vehicular fuel cell system. *Int. J. Hydrogen Energy* **2021**, *46*, 5714–5728.
38. Pablo, G.; Torreglosa, J.P.; Fernández, L.M.; Jurado, F. Viability study of a FC-battery-SC tramway controlled by equivalent consumption minimization strategy. *Int. J. Hydrogen Energy* **2012**, *37*, 9368–9382.
39. Xu, L.; Jianfeng, H.; Xiangjun, L.; Jianqiu, L.; Minggao, O. Distributed control system based on CAN bus for fuel cell/battery hybrid vehicle. In Proceedings of the 2009 IEEE International Symposium on Industrial Electronics, Seoul, Republic of Korea, 5–8 July 2009; IEEE: Piscataway, NJ, USA.
40. Lü, X.; Meng, R.; Deng, R.; Long, L.; Wu, Y. Energy economy optimization and comprehensive performance improvement for PEMFC/LIB hybrid system based on hierarchical optimization. *Renew. Energy* **2022**, *193*, 1132–1149. [CrossRef]
41. Li, S.; Han, X.-F.; Xu, Y.-P.; Razmjooy, N. Exergy analysis of a fuel cell power system and optimizing it with Fractional-order Coyote Optimization Algorithm. *Energy Rep.* **2021**, *7*, 7424–7433.
42. Zhi, Y.; Wang, W.; Wang, H.; Yildizbasi, A. Developed coyote optimization algorithm and its application to optimal parameters estimation of PEMFC model. *Energy Rep.* **2020**, *6*, 1106–1117.