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Optimal Energy Management for Hydrogen Economy in a Hybrid Electric Vehicle

Seydali Ferahtia [1], Hegazy Rezk [2,3,*], Rania M. Ghoniem [4], Ahmed Fathy [5,6], Reem Alkanhel [4] and Mohamed M. Ghonem [7]

[1] Laboratoire de Génie Electrique, Department of Electrical Engineering, University of M'sila, M'sila 28000, Algeria
[2] Department of Electrical Engineering, College of Engineering in Wadi Alddawasir, Prince Sattam bin Abdulaziz University, Wadi Alddawasir 11991, Saudi Arabia
[3] Electrical Engineering Department, Faculty of Engineering, Minia University, Minia 6111, Egypt
[4] Department of Information Technology, College of Computer and Information Sciences, Princess Nourah bint Abdulrahman University, Riyadh 11671, Saudi Arabia
[5] Electrical Engineering Department, Faculty of Engineering, Jouf University, Sakaka 72388, Saudi Arabia
[6] Electrical Engineering Department, Faculty of Engineering, Zagazig University, Zagazig 44519, Egypt
[7] Department of Computer, Faculty of Engineering, Mansoura University, Mansoura 35516, Egypt
* Correspondence: hr.hussien@psau.edu.sa

Abstract: Fuel cell hybrid electric vehicles (FCEVs) are mainly electrified by the fuel cell (FC) system. As a supplementary power source, a battery or supercapacitor (SC) is employed (besides the FC) to enhance the power response due to the slow dynamics of the FC. Indeed, the performance of the hybrid power system mainly depends on the required power distribution manner among the sources, which is managed by the energy management strategy (EMS). This paper considers an FCEV based on the proton exchange membrane FC (PEMFC)/battery/SC. The energy management strategy is designed to ensure optimum power distribution between the sources considering hydrogen consumption. Its main objective is to meet the electric motor's required power with economic hydrogen consumption and better electrical efficiency. The proposed EMS combines the external energy maximization strategy (EEMS) and the bald eagle search algorithm (BES). Simulation tests for the Extra-Urban Driving Cycle (EUDC) and New European Driving Cycle (NEDC) profiles were performed. The test is supposed to be performed in typical conditions t = 25 °C on a flat road without no wind effect. In addition, this strategy was compared with the state machine control strategy, classic PI, and equivalent consumption minimization strategy. In terms of optimization, the proposed approach was compared with the original EEMS, particle swarm optimization (PSO)-based EEMS, and equilibrium optimizer (EO)-based EEMS. The results confirm the ability of the proposed strategy to reduce fuel consumption and enhance system efficiency. This strategy provides 26.36% for NEDC and 11.35% for EUDC fuel-saving and efficiency enhancement by 6.74% for NEDC and 36.19% for EUDC.

Keywords: hybrid electric vehicles; energy management; energy efficiency; fuel cells; hydrogen

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1. Introduction

The demand for fossil fuels has grown during the industrial period. Burning fossil fuels has resulted in an increase in global carbon dioxide emissions, exacerbating global warming. According to the US department of energy (DoE), the transportation sector consumes more than 28% of the total electrical power [1]. As an alternative fuel, hydrogen may be created by reforming carbon-based fuels (grey and blue hydrogen) or by operating water with electricity generated from renewable resources (green hydrogen). Electric vehicles are a promising solution to decarbonize the transport sector [2]. The fuel cell hybrid electric vehicle (FCEV) is one of the most promising solutions that reduce carbon dioxide emissions.

FCEV technology combines an energy storage system (ESS) with hydrogen fuel cell(s) (FC) to supply an electrical motor [3]. FCEV technology provides better energy savings and fuel economy [4]. FCEV has many benefits, such as high performance with no pollutant emissions, quiet operation, small size, and no reliance on fossil fuels [5]. To achieve this, the US Department of Energy (DOE) has established two 2025 fuel cell standards that must be accomplished simultaneously: a cost target of 40$/kW net and a durability target of 5000 h. Targets for performance and longevity at their highest levels are 30$/kW net and 8000 h [6]. As a result, electric vehicles (EVs) are expected to be heavily incorporated into future smart grids due to their critical role in creating a safe environment and sustainable transportation sector [7].

Since the FCEV power system is entirely electrical, the ESS (batteries and/or supercapacitors) recover or provide high power peaks during braking or accelerating [8]. Because of the slow dynamics of the fuel cell and the limited battery charging/discharging cycles, hybridization with a high specific energy storage system, such as supercapacitors (SCs) that have fast dynamics, is required to overcome these issues and to enhance the overall performance [9]. The hybridization provides the FC system with better operating conditions, increasing FC system performance. This hybrid multisource system requires an energy management strategy (EMS) that controls the power flow to reduce fuel consumption and enhance system efficiency. In other words, the EMS functions as a power splitter for energy from both primary and auxiliary sources [10]. However, the primary concern in EMSs is the efficiency of the chosen strategy or control approach. To this end, different EMSs have been widely reported in the literature. EMSs can be divided into two classes [11]: rule-based and optimization-based EMSs.

Rule-based strategies represent strategies that depend on the operating system state. This class has two subclasses: deterministic rule-based and fuzzy rules-based. The state machine control strategy (SMC) is one most used deterministic rule-based [12]. However, fuzzy logic is the most adopted EMS in this category based on fuzzy logic controllers [13]. Although it is easy to design and implement, it is still based on the designer's knowledge, which limits its performance [14]. The optimization strategies are based on the objective function's minimization or maximization. There are two subclasses: offline (global) and online optimization strategies (real-time). Developing the EMS as an offline optimization problem involves solving an optimal control problem over an a priori known mission (speed profile). There are different approaches:

- Direct methods (disciplined optimal control).
- Indirect methods (Pontryagin's maximum principle (PMP) [15], calculus of variations [16]).
- Dynamic programming (DP) [17] and stochastic dynamic programming (SDP) [18].

These strategies require knowledge of the total load profiles, which results in enormous amounts of data to calculate. The decision of the online strategies is based on the evolution of objective function value, which makes them more robust with high performance. These strategies typically include equivalent consumption minimization strategy (ECMS) [19] and external energy maximization strategy (EEMS) [20]. Real-time strategies are necessarily suboptimal. ECMS is derived from optimal control theory. According to [21], the ECMS is designed and demonstrated based on the PMP strategy. The equivalent factor plays the same role as the co-state of the PMP approach. So ECMS with a constant co-state is an optimal solution to the offline optimization problem [22]. Since the EEMS system aims to maximize the power that comes from the SC and the battery, the overall system efficiency will be implicitly improved. In addition, the FC has limited dynamics and supplies only the steady state load. The SC and the battery are the sources that meet the transitory loads. Hence, this will enhance the system's efficiency.

A set of published works are listed in Table 1. This table includes the details of each reported EMS such as the used EMSs, the advantages, the drawbacks, and its application either online or offline. Most of the reported works in this table use the online strategy. This can be explained by the ability of online strategies to adapt to various operating conditions.

Table 1. Summary of some published works.

Reference	EMS	Advantages	Drawbacks	Application
Li and Liu [10]	Fuzzy logic	Highest efficiency.	Dynamic problems are not included.	Online
E. Pukkunnen et al. [23]	Hybrid fuzzy reinforcement learning	Training the FL-based EMS enables HEV to operate with reduced energy loss and enhanced efficiency.	It requires training data. It requires high calculators.	Online
Y. Lui et al. [24]	Imitation reinforcement learning-based algorithm	Reduced data training and requirement of the prediction of future operation states.	Offline optimization enables optimality. However, keeping adaptivity in real-time applications is challenging.	Online
B. Tormos et al. [25]	Offline dynamic programming	Reduce fuel consumption while protecting the battery.	Offline optimization cannot guarantee optimality in cases out of the expected ones.	Offline
D. Min et al. [26]	Neural network with genetic algorithm	Prolonged lifespan of the fuel cell.	It requires training data.	Online
Ouddah et al. [27]	Frequency decoupling PMP	DC bus voltage is smoother using the PMP strategy.	Power converter losses were ignored.	Online
Garcia et al. [28]	SMC Cascade PI control Fuzzy logic ECMS Predictive control	In comparison, ECMS has the lowest hydrogen mass usage.	Power generation was 400 kW, although demand power showed 500 kW.	Online
Zandi et al. [29]	Flatness control strategy (FLC) Fuzzy logic	FLC calculates power-sharing coefficients for SC and battery.	Neglecting cable inductance and capacitor series resistance.	Online
Matopan et al. [30]	SMC Fuzzy logic classical PI frequency decoupling ECMS	Classical PI provides the lowest hydrogen consumption and second lowest battery stress, and SMC has the highest efficiency and lowest battery stress.	Only hydrogen consumption and stress analysis were considered as comparison points.	Online
Uzunoglu and Alam [31]	Wavelet-based algorithm	The results demonstrate the role of the SC in providing quick switching of voltage-positive and -negative terminals.	It does not include a battery.	Online
Ates et al. [32]	Artificial neural network (ANN)	SC effectively smooths charging and discharging power demand fluctuations.	It does not include a battery.	Online
M. Iqbal et al. [33]	Dual-layer approach for systematic sizing and online EMS	The online optimizer adjusts the power-splitting rules of distinct layers, which decreases fuel consumption and system health degradation.	Double-layer online optimization may require high computing calculators for real-world applications.	Online

Several studies confirmed that hybridizing metaheuristic algorithms (MAs) and online EMSs could provide the best performance. These algorithms have gained enormous popularity in these engineering applications [34]. Hegazy et al. [35] proposed an optimized version of ECMS and EEMS based on the mine blast algorithm (MBA) and the salp swarm algorithm (SSA). The combination between the SSA and EEMS provides optimal efficiency and fuel consumption performance. A similar comparative study was performed by

Zhao et al. [36]; in this paper, different meta-heuristic optimization algorithms were used, including the artificial bee colony (ABC), grey wolf optimization (GWO), electromagnetic field optimization (EFO), cuckoo search (CS), MBA, moth swarm algorithm (MSA), harmony search (HS), modified flower pollination algorithm (MFPA), and whale optimization algorithm (WOA). The obtained results provide the optimized EEMS with the GWO over the ECMS and its optimized versions. Genetic fuzzy-based EMS was proposed in [37] to improve fuel economy. Optimized EMS based on the genetic algorithm was proposed in [38]. This paper includes a review of different FCEV topologies.

The FC/battery used topology has been used in the literature; its benefits were approved [39]. However, introducing the SC can enhance the battery lifecycle due to its fast dynamics. In addition, this paper provides and approves an optimized version of the EEMS that requires an SC connected to the DC bus. For these reasons, the FC (FPEMC)/battery/supercapacitor FCEV semi-active topology was chosen. The studied power system is illustrated in Figure 1. The proposed EMS is optimized by a modern optimization MA called the bald eagle search (BES) algorithm. The BES algorithm has provided excellent performance for many online and offline applications compared to other classical and recent algorithms ([40–42]). This high performance is due to a unique updating mechanism that uses three phases: select space, search in the space, and swooping. Each phase contributes effectively to finding the optimal results. In this study, it is assumed that the battery state of charge (SoC) is known (measurable), as well as the load demand. The main contribution of this study is to benefit from the high performance of the BES to reduce hydrogen consumption while improving the electrical efficiency of the power system. This paper presents the first use of this algorithm in this kind of application. Its practical applicability can provide the EV with a better driving experience where the economized fuel can allow longer driving distances, and the enhanced efficiency enables better energy economy. The proposed EMS is compared in terms of fuel consumption and system efficiency with the original EEMS and particle swarm optimization (PSO) [43] and equilibrium optimizer (EO) [44]. To make it clear, the main contribution of this paper is in providing an optimized version of the conventional EEMS that effectively reduces fuel consumption while enhancing electrical efficiency.

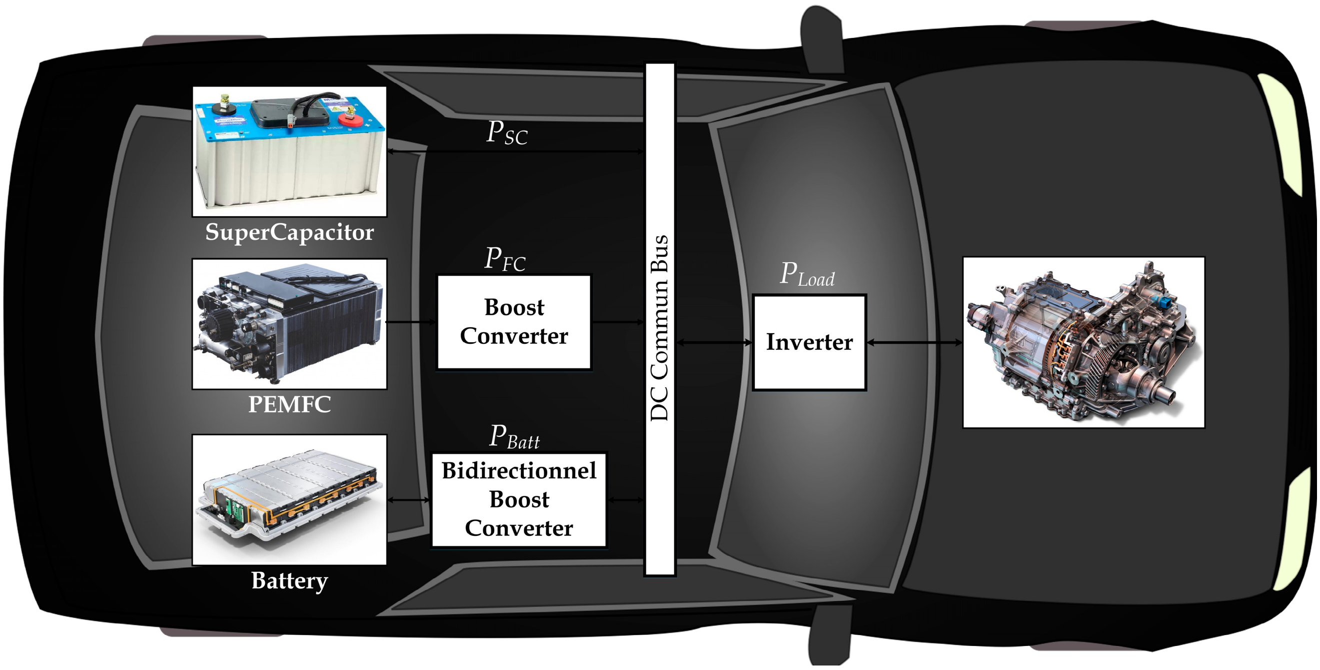

Figure 1. The FHEV power system topology.

The rest of the paper is organized as follows: Section 2 presents the FCEV architecture, including the used mathematical models; Section Section 3 explains the energy management strategy, including the EEMS and the BES algorithms; the results and discussion are provided in Section 4, including the simulation results and analysis; this paper ends with a conclusion in Section 5.

2. FCEV Architecture

As illustrated in Figure 1, the FCEV is powered by three energy sources: proton exchange membrane fuel cell (PEMFC) as the primary source, lithium-ion battery, and supercapacitor energy storage systems (EESs). The fuel cell is connected to the DC bus through a unidirectional DC/DC boost converter. A bidirectional DC/DC boost is used to connect the battery. The SC is connected directly to the DC bus. On the other side, the vehicle motor is supplied utilizing a bidirectional DC/AC inverter that allows the power to flow in two directions, from the DC bus to the motor in the traction case and the opposite in the breaking case.

2.1. Vehicle Traction Model

The traction force can be calculated according to the physical forces applied to the vehicle body as follows [45]

$$F_T = F_m + F_r + F_{ad} + F_U \tag{1}$$

where F_T is the traction force, F_r is the rolling resistance force, F_{ad} is the aerodynamic force, F_U is the gradeability or uphill driving force, and F_m is the motor force. Each force can be calculated as follows

$$F_{ad} = \frac{1}{2}\rho v^2 A C_d \tag{2}$$

where ρ is the air density; v is the vehicle speed; A is the frontal area; C_d is the drag coefficient.

$$F_r = c_r m_v g \cos(\alpha) \tag{3}$$

where m_v is the vehicle mass; g is the gravity acceleration; cos(α) represents the influence of a non-horizontal road; α is the read slop; c_r is the rolling friction coefficient depending on the vehicle speed, tire pressure, road surface conditions, etc.

$$F_U = m_v g sin(\alpha) \tag{4}$$

$$F_m = M_{equi} a = \left(m_v + J_{em} \frac{\rho^2}{R_{tire}^2} \right) \frac{dv(t)}{dt} \tag{5}$$

where a is the acceleration, J_{em} is the motor inertia, R_{tire} is the tire radius. An illustration of these forces is presented in Figure 2.

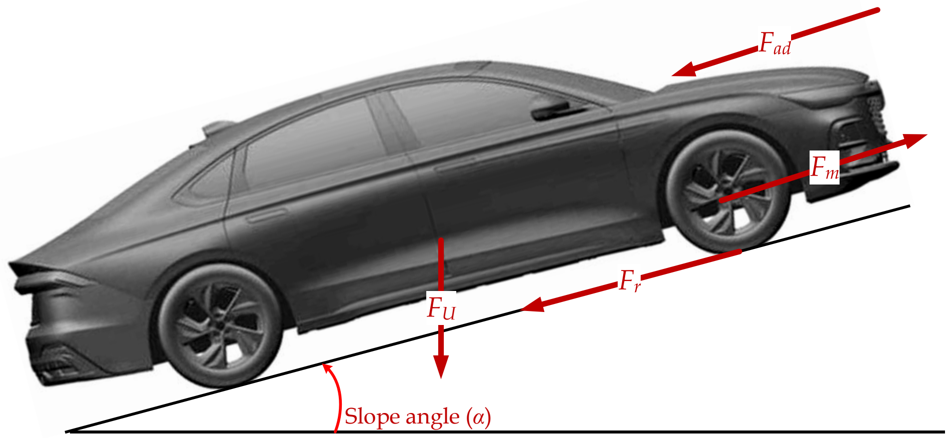

Figure 2. The FHEV power system topology.

From Equation (1), the required power by the traction motor on the DC bus can be calculated as follows [46]

$$P_{load}(t) = P_T(t) \cdot \eta = v(t) \cdot F_T(t)\eta_{mot} \cdot \eta_{inv} \cdot \eta_{trans} \tag{6}$$

where η_{mot} and η_{trans} are the electrical and mechanical transmission efficiencies, respectively, η_{inv} is the inverter efficiency, and $v(t)$ is the DC bus voltage.

2.2. FC hydrogen Consumption Model

FC is an electrochemical device that converts the converter chemical energy of hydrogen and oxygen to electrical power. According to [47], hydrogen consumption is related to the FC output current as follows

$$C_{H_2} = \int_0^t \frac{M_{H_2} n_{cell}}{2F} i_{FC}(t)dt \tag{7}$$

where C_{H2} describes the hydrogen consumption rate (g/s), n_{cell} is the number of cells, M_{H2} denotes the hydrogen molar mass (2.02 g/mol), i_{FC} is the FC output current (A), and F is the Faraday constant (96, 487 C).

2.3. Battery State of Charge Estimation Model

According to the published works in [48], the battery state of charge (SoC) can be calculated as follows

$$SoC(t) = SoC_0 - \frac{1}{Q}\int_0^t iBatt(t)dt \tag{8}$$

where SoC_0 is the initial SoC (%), Q is the nominal battery capacity (Ah), and i_{Batt} is the battery current (A).

3. The Proposed Energy Management Strategy

The energy management strategy was developed to minimize fuel consumption, extend the battery and supercapacitor lifespans, and maximize overall efficiency.

3.1. Problem Formulation

As mentioned above, the EEMS is an RTO strategy that aims to minimize fuel consumption by maximizing the battery and SC energy requests within their operational limitations [20]. Therefore, the studied problem is an optimization problem where the objective function to minimize (J) is given in Equation (9), and the decision variables are $v = [P_{Batt}, \Delta V]$. The objective function can be formulated as

$$J = -\left(v_1 \mathrm{Ts} + {}^1\!/_2 \mathrm{C}_{SC} {v_2}^2\right) = -\left(P_{Batt}\mathrm{Ts} + {}^1\!/_2 \mathrm{C}_{SC}\Delta V^2\right) \tag{9}$$

P_{Batt} is the battery power, Ts is the sampling time, ΔV is the charge/discharge voltage, and C_{SC} is the SC-rated capacity. The decision variables are bounded as

$$\begin{array}{c} P_{Batt}^{\min} \le v_1 \le P_{Batt}^{\max} \\ \Delta V_{\min} \le v_2 \le \Delta V_{\max} \end{array} \tag{10}$$

where P_{Batt}^{min} and P_{Batt}^{max} are the battery's min and max output power, V_{dc}^{min} and V_{dc}^{max} are the min and max DC bus voltage limits.

This objective function is submitted to the following constraint

$$P_{Batt}\mathrm{Ts} \le (\mathrm{SoC} - \mathrm{SoC}_{\min})\mathrm{V}_{Batt} Q_{Batt} \tag{11}$$

SoC is the battery state of charge, $\mathrm{SoC}_{\min}$ is the battery's lower SoC, V_{Batt}, and Q_{Batt} are the battery voltage and capacity, respectively. This equation determines the maximum possible power by considering the difference between the actual SoC and its minimum limit value. The optimization variables have the following constraints.

The power reference for the battery and the FC can be formulated as follows

$$\begin{gathered} P_{Batt}^{ref} = v_1 \\ P_{FC}^{ref} = P_{load} - P_{Batt}^{ref} \end{gathered} \quad (12)$$

In fact, the DC bus voltage is regulated using the battery system. The PI regulator generates the battery power reference and ensures a stable DC bus voltage [30]. The operating scheme is illustrated in Figure 3.

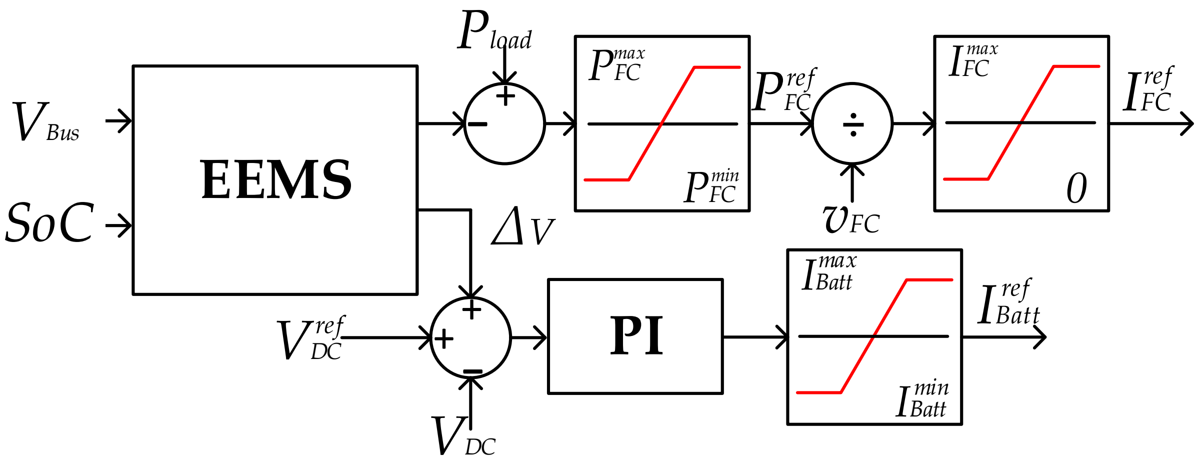

Figure 3. EEMS scheme.

3.2. Bald Eagle Search Algorithm

The bald eagle search (BES) algorithm is a recent metaheuristic optimization algorithm (MA) that was inspired by the searching and hunting strategy of the bald eagle [49]. The fundamental idea of BES is to simulate the movement and hunting process of a bald eagle hunting process. Mainly, there are three phases: select space, search, and swooping.

1. Select space: the eagle starts from random positions and searches to detect prey space based on the following equation

$$P_{new} = P_{best} + \alpha.r.(P_m - P) \quad (13)$$

where P_{new} is the newly generated positions, P_{best} is the prey location (best position), α is a controlling factor [1.5,2], and r is a random number in [0,1], P_m is the mean of the current positions. According to the fitness of the new positions, P_{best} will be updated.

2. Searching in the space: In this phase, the eagle explores the search space as follows

$$P_{new}(i) = P(i) + y(i).(P(i) - P(i+1)) + x(i).(P(i) - P_m) \quad (14)$$

where $P_{new}(i)$ is the i-th newly generated positions, x and y are their directional coordinates that can be defined as

$$\begin{gathered} \begin{cases} r_x(i) = r(i).\sin(\theta(i)) \\ r_y(i) = r(i).\cos(\theta(i)) \end{cases} \\ \begin{cases} x(i) = \frac{r_x(i)}{\max(|r_x|)} \\ y(i) = \frac{r_y(i)}{\max(|r_y|)} \end{cases} \\ \theta(i) = a.\pi.rand; \;\; r(i) = \theta(i).R.rand \end{gathered} \quad (15)$$

where r is the radius and r_x and r_y are its comports, x and y can be obtained by normalizing r_x and r_y, a is a controlling factor utilized to determine the corner between point search in the central point, it takes value in [5, 10], R is a parametric gain in [0.5, 2] utilized to determine the number of search cycles. P_{best} value will be updated according to the obtained fitness of P_{new}.

3. Swooping: the eagle suddenly attacks the prey from the best-obtained position according to the following equation

$$P_{new}(i) = rand.P_{best} + x1(i).(P(i) - c_1.P_{mean}) + y1(i).(P(i) - c_2.P_{best}) \tag{16}$$

where c_1 and c_2 are random factors [1, 2], P_{mean} is the mean of the current positions, $x1$ and $y1$ are the directional coordinates of each position. They can be expressed as

$$\begin{aligned} x1(i) &= \tfrac{xr(i)}{\max(|xr|)}; \;\; xr(i) = r(i).\sinh(\theta(i)) \\ y1(i) &= \tfrac{yr(i)}{\max(|yr|)}; \;\; yr(i) = r(i).\cosh(\theta(i)) \\ \theta(i) &= a.\pi.rand; \;\; r(i) = \theta(i) \end{aligned} \tag{17}$$

The BES will be used to optimize the EEMS objective function. The main objective is to minimize fuel consumption and enhance the overall efficiency compared with the original EEMS. The BES flowchart is illustrated in Figure 4.

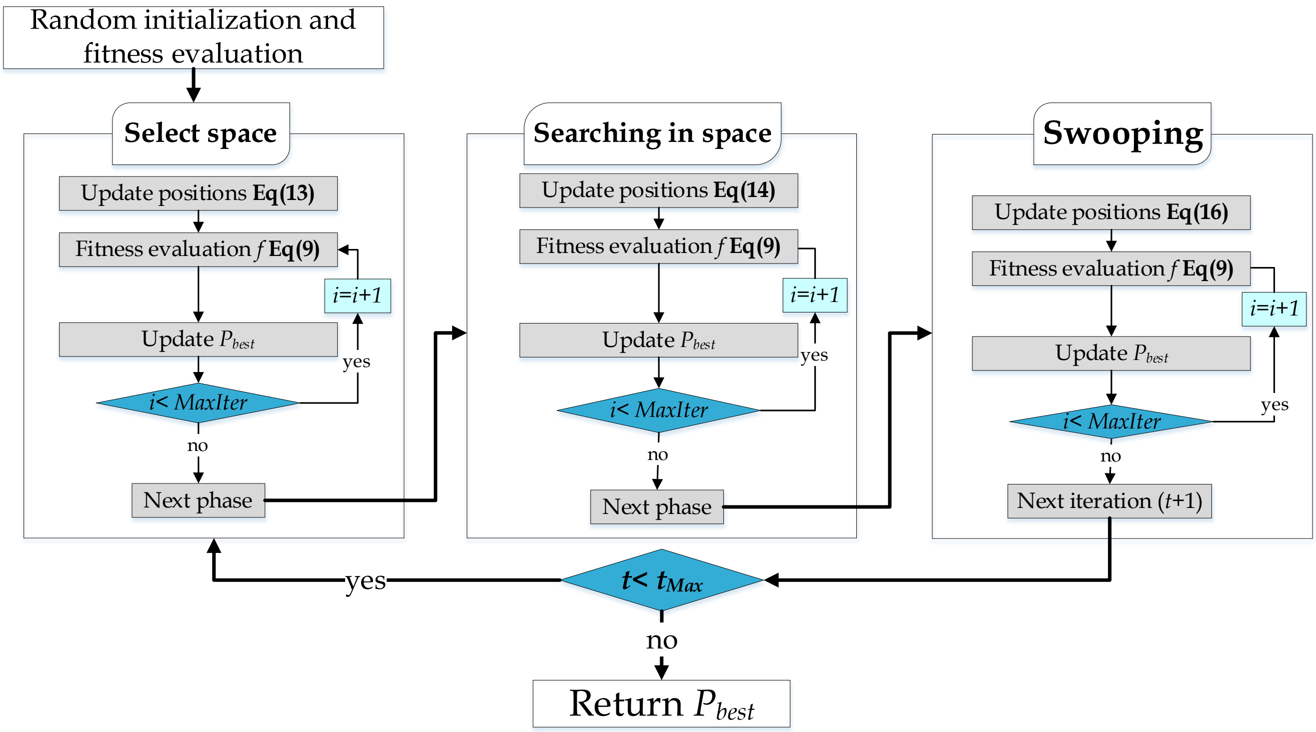

Figure 4. BES flowchart.

The bald eagle search algorithm, similar to the other metaheuristic optimization algorithms, can be employed in online applications. At each iteration, the BES sends the candidate solutions to the system, and then the system reaction will send back to it through a zero-order hold block (ZOH). Based on the received feedback, the optimizer updates the positions and sends them again to the system to evaluate their effect on the system's performance and determine the best one among them. This online optimization manner is similar to the one reported in [35].

4. Results and Discussion

To assess and validate the performance of each strategy, a simulation model was built in Matlab/Simulink environment. The elements, including the converters and the sources, are modeled using SimPowerSystem blocks. The performance of the studied EMS is evaluated for the Extra-Urban Driving Cycle (EUDC) and New European Driving Cycle (NEDC) speed profiles [45]. Table 2 presents the characteristics of each driving cycle. The speed and motor power profiles for both NEDC and EUDC are shown in Figures 5 and 6, respectively. The proposed EMS was tested in a similar system used in [30]. The simulation is performed under several assumptions including the typical conditions t = 25 °C on a flat road without including the wind effect. In addition, the machine side is not included in the traction system to simplify the global model and accelerate the simulation.

Table 2. Driving cycle characteristics.

	EUDC	NEDC	Unit
Time	400	1184	sec
Distance	6.95	10.93	km
Max speed	120	120	km/h
Average speed	62.59	33.21	km/h
Max acceleration	0.833	1.06	m/s^2
Min acceleration		−1.39	m/s^2
Average acceleration	0.354	0.54	m/s^2
Average deceleration		−0.79	m/s^2
Idle time	39	298	sec
Number of stops	1	13	

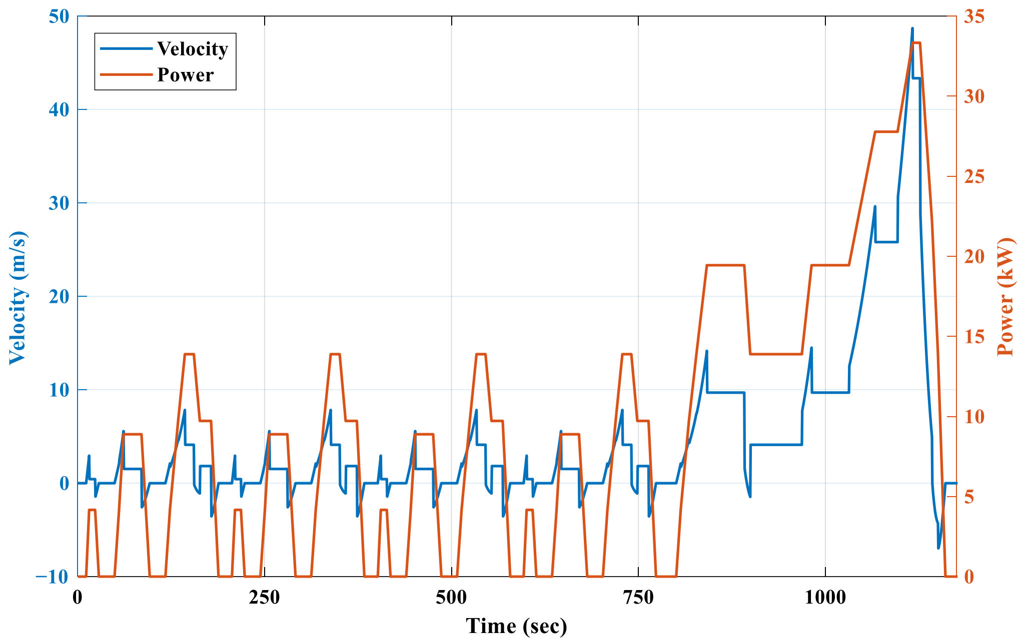

Figure 5. NEDC driving cycle velocity and power profiles.

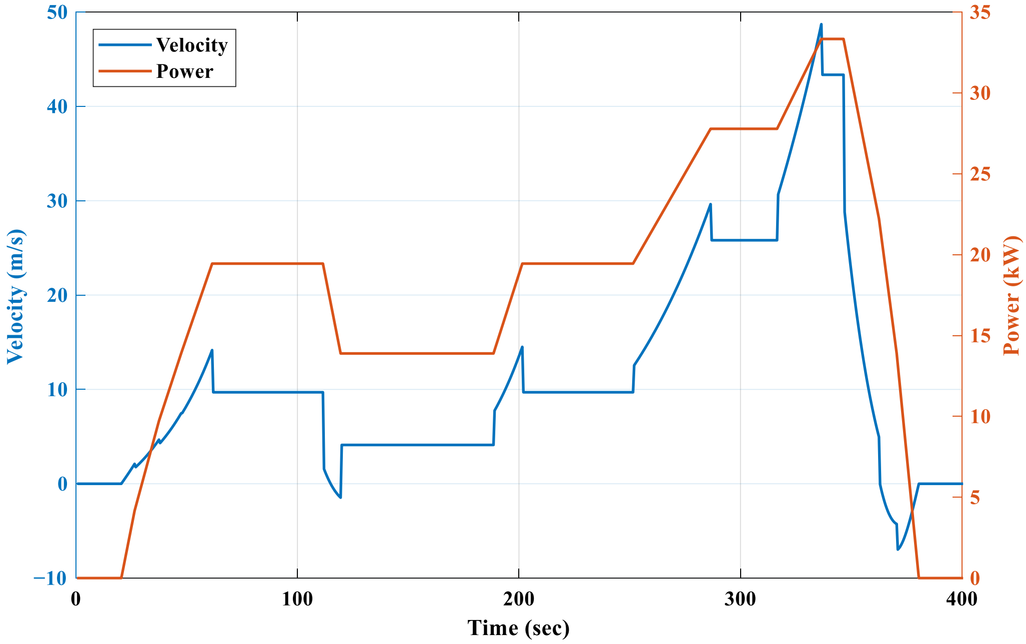

Figure 6. EUDC driving cycle velocity and power profiles.

Average models have been used to represent the converters. Thus, efficacy is supposed to be constant. On the other hand, the vehicle parameters are presented in Table 3.

Table 3. Vehicle parameters.

Element	Value	Unit
PEMFC	30–60	V
	12.5	kW
Li-ion Battery	48	V
	40	Ah
Supercapacitor	Six series-connected caps	
	15.6	F
	291.6	V
FC boost converter	12.5	kW
	η = 85	%
Battery boost converter (for discharging)	4	kW
	η = 88	%
Battery buck converter (for charging)	1.2	kW
	η = 88	%
Motor inverter	15	kVA
	200	V AC
	400	Hz
	η = 97	%
Vehicle		
Weight (m_v)	579	kg
Frontal surface area (A)	2.48	m^2
Density of air (ρ)	1.26	kg/m^3
Drag coefficient (C_d)	0.7	
Rolling resistance coefficient (c_r)	0.015	
Mechanical transmission efficiency (η_{trans})	0.92	
the gravitational acceleration (g)	9.81	m/s^2
Inclining angle (α)	0°	

The proposed EMS is compared with the state machine control strategy (SMCS), equivalent consumption minimization strategy (ECMS), and classic PI control strategy. The PI regulator generates the battery power reference, which is then subtracted from the load power to obtain the fuel cell reference power. The PI gains the same with [30]. These parameters are included in More Electric Aircraft in the Matlab/Simulink library.

Furthermore, the proposed EEMS-based BES will be compared with EEMS minimized by the *fmin* function, PSO-based EEMS, and EO-based EEMS to validate its performance. The population size for each algorithm is set at five, and the max number of iterations is 100.

Figure 5 presents the velocity and the corresponding traction load power for the NEDC case. As illustrated in this figure, the speed significantly increases after the 800th second to the end of the profile. The power changes according to the velocity changes. Figure 6 presents the evolution of the speed and power for the EUDC driving cycle. The variation of the speed, in this case, is reduced compared to the case of the NEDC.

4.1. NEDC Case

The power sources, including the load, are displayed in Figure 7, employing the EEMS. The fuel flow rate and consumption for SMCS, PI, ECMS, and EEMS are represented in Figure 8. The SC power, which expresses the bus power, decreases if the load power decreases to absorb the excess power generated by the slow dynamic system (mainly the FC). In the load-increasing case, the SC provides the required power for a limited transition time until the battery and the FC reach their power references.

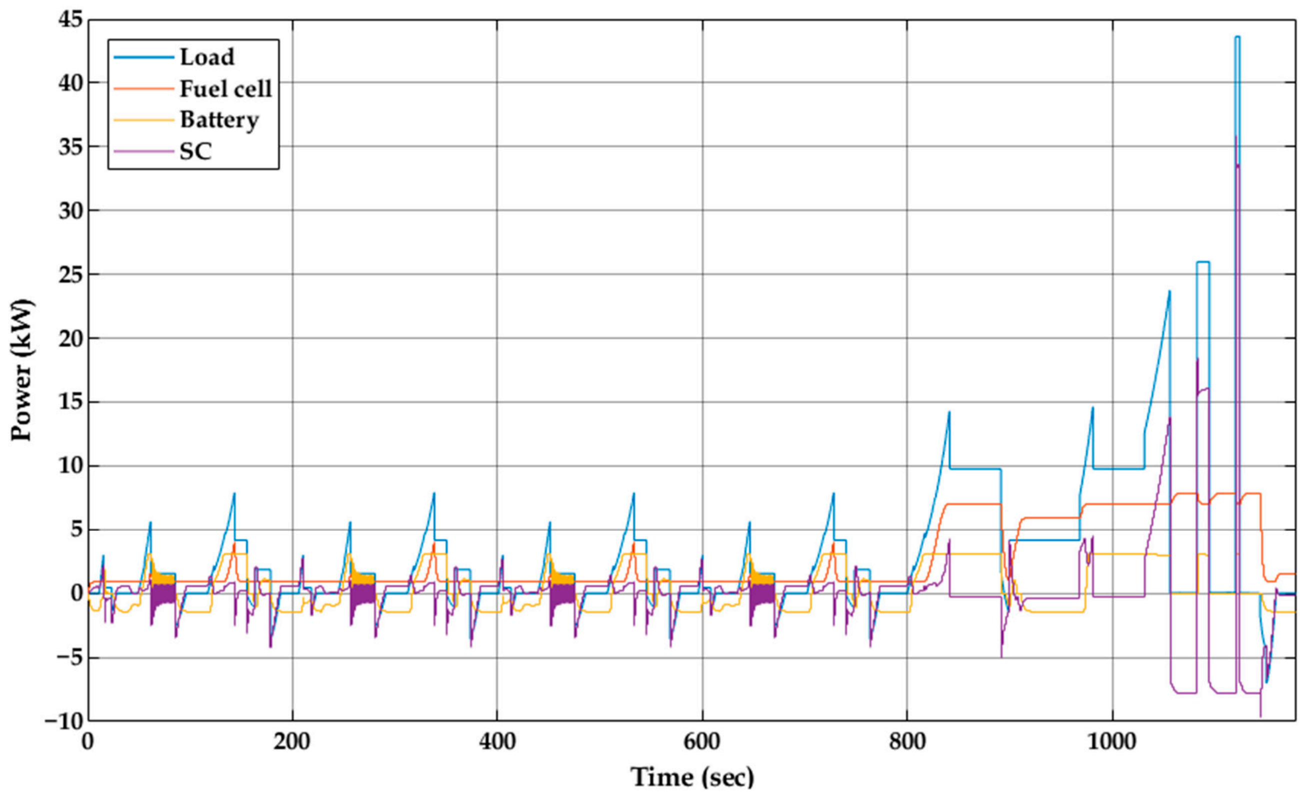

Figure 7. Load, FC, battery, and SC power using EEMS for NEDC.

As illustrated in Figure 7, the FC supplies most of the load slowly due to its limited dynamics, which are related to its chemical reactions. The battery balances the power in the DC bus. It absorbs the excess power and supports FC in case of a deficit. The SC provides DC bus voltage smoothing by supplying the transit periods. Its mean power is zero in the steady state case.

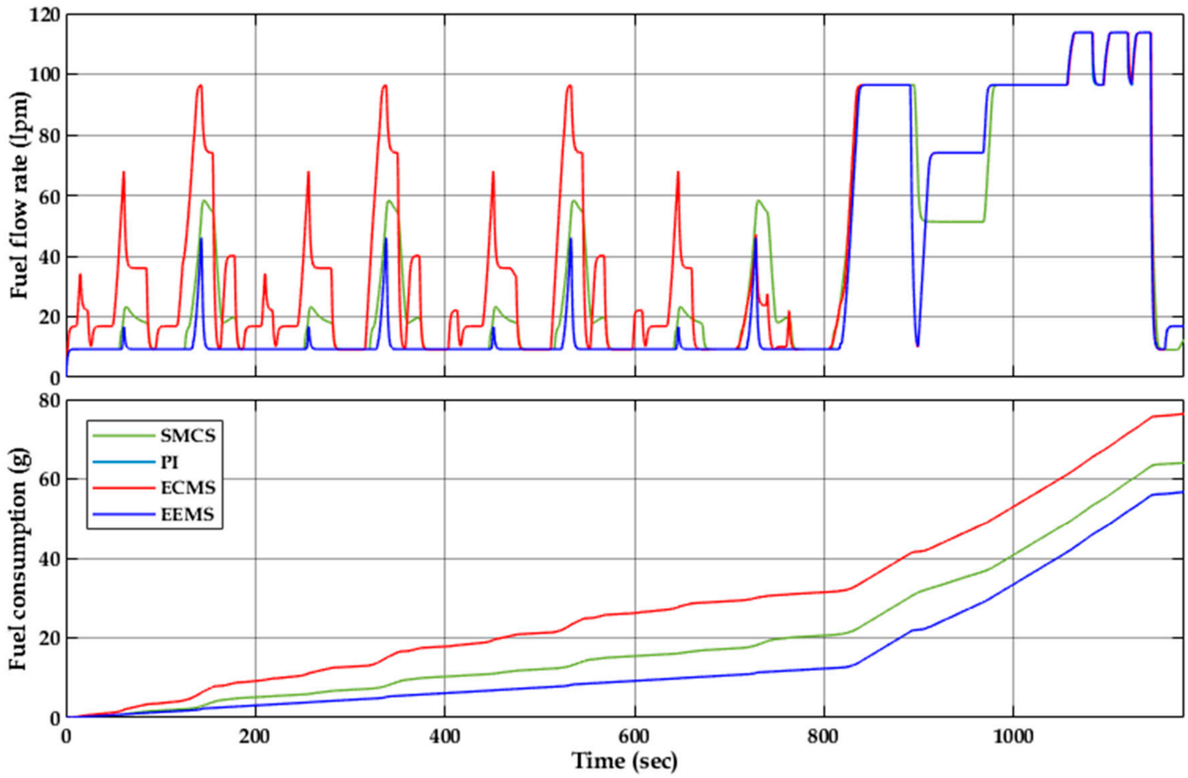

Figure 8. Fuel flow rate and fuel consumption for SMCS, PI, ECMS, and EEMS for NEDC.

Compared with the other strategies, the EEMS can successfully reduce fuel consumption, as illustrated in Figure 8. The fuel consumption evolution is slower compared to the other strategies. This advantage can be explained by its objective function, which maximizes the energy from the auxiliary sources, such as the battery, to contribute to minimizing fuel consumption.

Focusing on the EEMS, the EEMS-based *fmin*, PSO, EO, and BES results are illustrated in Figure 9. The top figure illustrates the fuel flow rate (FFR), and the bottom one shows the cumulative fuel consumption. The FFR achieves its max level during peak times because of the high demand for power from the traction system. As mentioned before, the FC supplied most of this load. Therefore the consumed fuel curve rises quickly during these times. EEMS-based PSO and EO do not perform better than the conventional EEMS, whereas the EEMS-based BES effectively reduces the FFR and the cumulative fuel consumption as illustrated at the end of these curves (from t = 850 to t = t_{end}). Simulation statistics are presented in Table 4 to analyze the achieved results better. This table includes the consumed fuel, the electrical efficiency, and the battery's final state of charge. The best results are marked in bold. The electrical efficiency expresses the losses efficiency in the power system. It can be calculated as a ratio between the traction system power and the total provided power as follows

$$\eta_{total} = \frac{P_{mot}}{P_{FC} + P_{Batt} + P_{SC}} 100 \tag{18}$$

The proposed EMS (EEMS-BES) successfully reduced the fuel consumption to 48.41 g compared to the conventional EEMS (65.71 g) and the other considered strategies. At the same time, it provided a higher electrical efficiency performance of 79.84%. The SMC strategy provides the second-best result concerning fuel consumption with 64.05 g, whereas the conventional EEMS provides the second-best efficiency with 74.80%. This confirmed its ability to reduce consumed hydrogen and enhance efficiency.

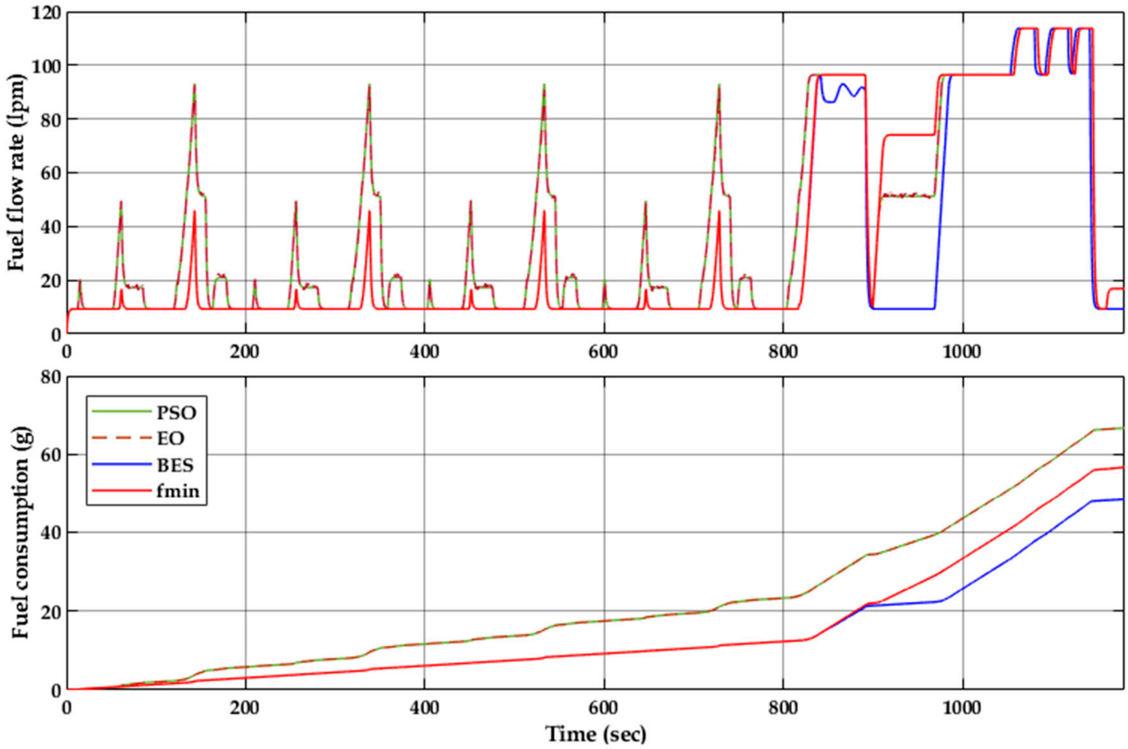

Figure 9. Fuel flow rate and fuel consumption for EEMS-based *fmin*, PSO, EO, and BES for NEDC.

Table 4. Simulation results.

Strategy	Fuel Consumption (g)	Electrical Efficiency (%)	Final SoC (%)
SMCS	64.05	64.90	59.01
PI	66.74	49.01	52.30
ECMS	76.38	39.80	**66.38**
EEMS	65.71	74.80	52.39
EEMS-PSO	66.69	55.79	62.08
EEMS-EO	66.68	56.80	62.07
EEMS-BES	**48.41**	**79.84**	47.11

4.2. EUDC Case

The power sources, including the load, are displayed in Figure 10, employing the EEMS. The fuel flow rate and consumption for SMCS, PI, ECMS, and EEMS are represented in Figure 11. EEMS-based *fmin*, PSO, EO, and BES are illustrated in Figure 12.

The load fluctuations are lower compared with the NEDC case. FC, battery, and SC dynamics are more explicit in this figure, where the FC supplies the most load, the battery balances the power in the DC bus, and the SC provides the transit periods. The simulation results are presented in Figures 11 and 12, and their corresponding statistics are presented in Table 5. At the first 20 s, the load is minimal, the FC operates at its lower rate, and the battery starts charging. After 30 s, the constant switching between the battery and the supercapacitor is related to the optimizer output signals. The optimizer starts from random positions and sends them to the power system as candidate solutions. The optimizer converges to the optimal solutions based on the recorded feedback from the system. At t = 280 s, the load is down. However, the required power by the bus, expressed by the SC power, is still high due to the SC discharging. At this moment, the FC charges the SC. At t = 303 s, the load suddenly rises, which will be supplied quickly by the SC and the battery.

This large amount provided by the SC and the battery reduces the demand on the FC for a short time. At t = 365 s, the load power becomes negative due to the breaking power. This extra power will charge the battery.

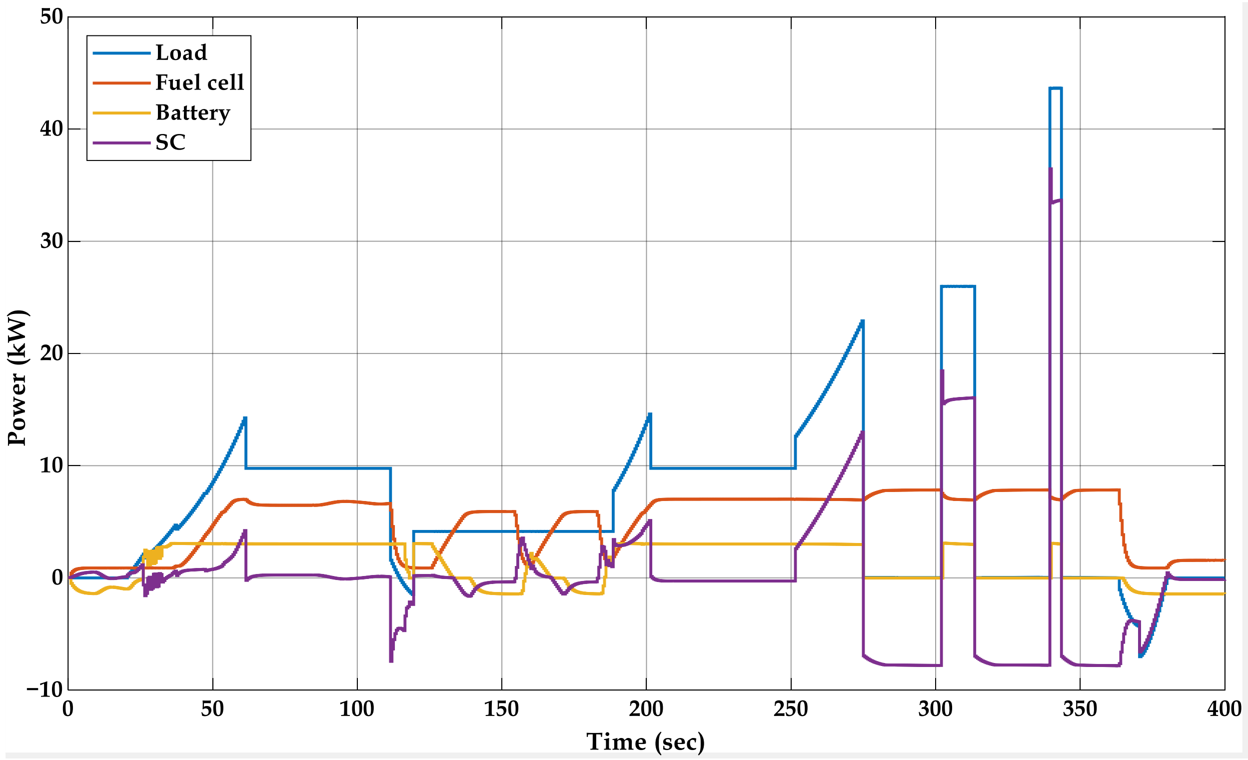

Figure 10. Load, FC, battery, and SC power using EEMS for EUDC.

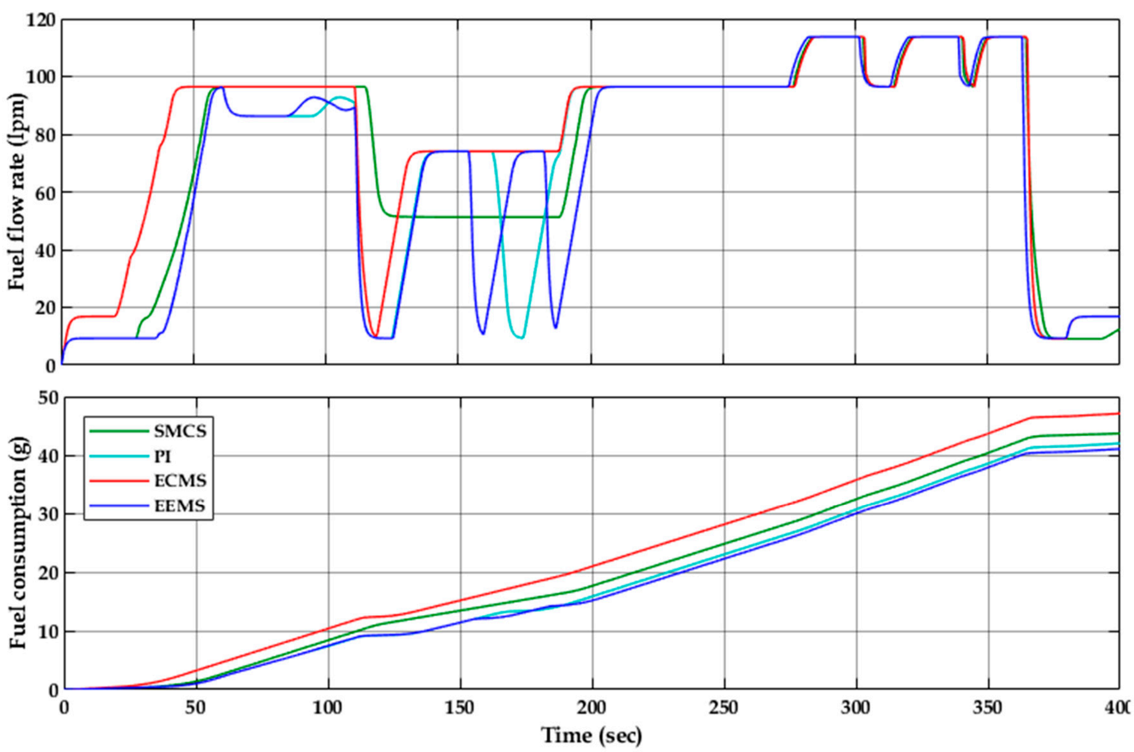

Figure 11. Fuel flow rate and fuel consumption for SMCS, PI, ECMS, and EEMS for EUDC.

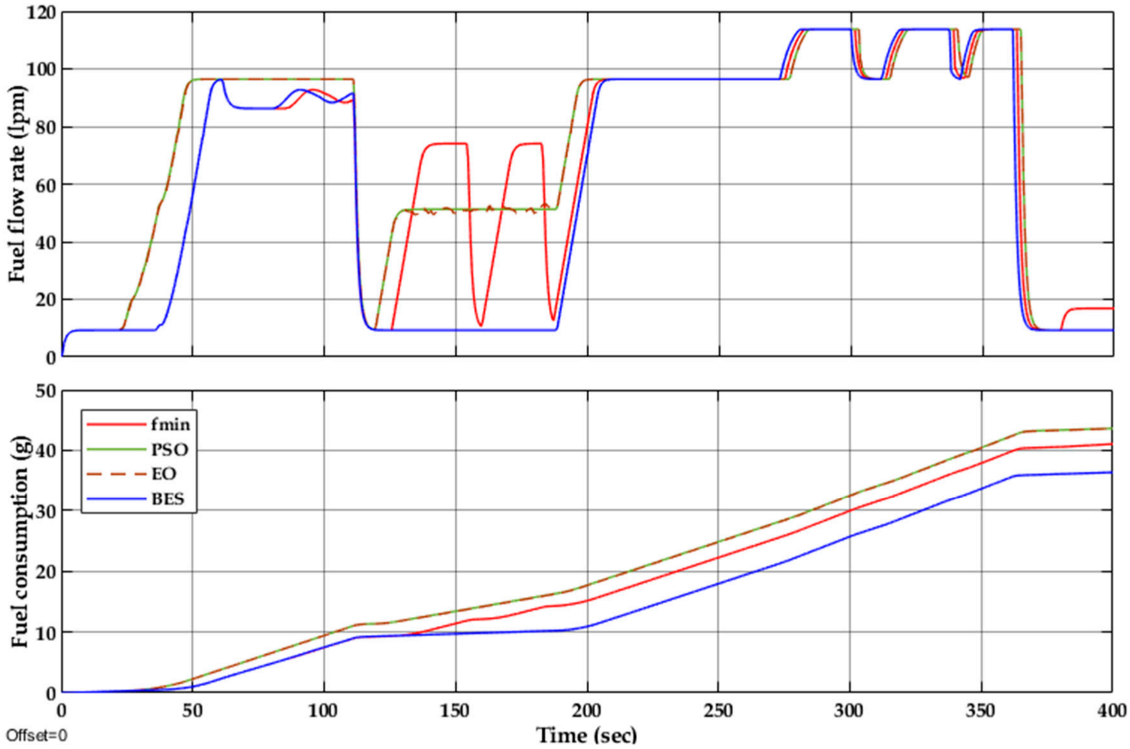

Figure 12. Fuel flow rate and fuel consumption for EEMS-based *fmin*, PSO, EO, and BES for EUDC.

Table 5. Simulation results.

Strategy	Fuel Consumption (g)	Electrical Efficiency (%)	Final SoC (%)
SMCS	43.71	47.82	56.39
PI	42	42.84	54.64
ECMS	47.11	42.93	**58.27**
EEMS	41.05	44.93	54.84
EEMS-PSO	43.63	47.87	56.73
EEMS-EO	43.59	47.96	56.70
EEMS-BES	**36.39**	**70.41**	51.49

Figures 11 and 12 show the variations in the fuel flow rate (FFR) and the evolution of the consumed hydrogen as a function of time. Similar to the results obtained in the NEDC case, the proposed EEMMS minimized fuel consumption compared to the other common strategies. The EEMS-BES also provides better results compared with the other EEMS versions. In Table 5, the best results are marked in bold. The proposed method results are the best in terms of fuel consumption and electrical efficiency.

The proposed EMS (EEMS-BES) proves its best performance compared to the other strategies regarding fuel consumption and electrical efficiency. The total consumed fuel was reduced to 36.39 g during the driving cycle, and efficiency equals 70.41%. The conventional EEMS follows it in terms of fuel consumption (41.05 g), and the EEMS-EO provides the second-best results regarding electrical efficiency. This second test approves the ability and robustness of the proposed strategy to meet predefined objectives, fuel reduction, and efficiency enhancement.

To ultimately approve the performance of the proposed EMS, Table 6 provides comparison results between the proposed EEMS-BES and the other common strategies. For the fuel-saving column, each value represents the fuel-saving ratio compared to each strategy (PI, SMC, ECMS, and conventional EEMS). In contrast, the efficiency enhancement represents the gain ratio compared to each strategy.

Table 6. Statistical results of the optimized EEMS-BES compared to other strategies.

Compared to	NEDC		EUDC	
	Fuel Saving (%)	Efficiency Enhancement (%)	Fuel Saving (%)	Efficiency Enhancement (%)
PI	27.64	38.61	16.75	39.16
SMCS	24.42	18.71	13.36	32.08
ECMS	36.62	50.10	22.76	39.03
EEMS	26.33	6.74	11.35	36.19

Compared to the method reported in [30], the proposed EMS successfully reduced the consumed fuel and enhanced the electrical efficiency. The performance of the proposed EMS has been approved from these results in both fuel saving compared to the classical EEMS (26.33% for the NEDC case and 11.35% for EUDC) and efficiency enhancement (6.74% for the NEDC case, 36.19% for EUDC).

5. Conclusions and Future Works

This paper presents an optimal energy management strategy (EMS) for fuel cell hybrid electrical vehicles (FCEVs) that was designed to ensure optimum power distribution between the sources, considering fuel consumption minimization and enhancing electrical efficiency. The proposed EMS is an optimized version of the external energy maximization strategy (EEMS) employing the bald eagle search (BES) algorithm. To approve the performance of the proposed EMS, a comparative simulation was performed for Extra-Urban Driving Cycle (EUDC) and the New European Driving Cycle (NEDC) profiles. Furthermore, this strategy was compared with the state machine control strategy (SMCS), classic PI, equivalent consumption minimization strategy (ECMS) EEMS based on *fmin* function, particle swarm optimization (PSO)-based EEMS, and equilibrium optimizer (EO)-based EEMS. Finally, fuel consumption and electrical system efficiency were compared. The obtained results approve the ability of the proposed strategy to reduce fuel consumption by 26.33% for NEDC and 11.35% for EUDC and enhance system efficiency by 6.74% for NEDC and 36.19% for EUDC. The increased complexity of the BES may require a fast-resolving calculator, which may increase the installation cost of this strategy in real-world applications. However, the cost of these calculators may decrease with technological advancement. Moreover, the results provided by the PSO and the PO are worse than the conventional EEMS. This can be explained by the no-free lunch theory (NFL), where no optimization algorithm can provide good performance for all optimization problems.

This study intends to reduce fuel consumption and increase the power system's global efficiency. Considering the battery SoC is a challenging task, this will be investigated as a multi-optimization problem in our future works. In addition, analyzing the power losses can be a critical factor in optimizing performance. This will be investigated in our future works.

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Nomenclature

FCEV	fuel cell hybrid electric vehicle
FC	fuel cell
PEMFC	proton exchange membrane FC
C_{H2}	consumed hydrogen
FFR	fuel flow rate
SC	supercapacitor
EES	energy storage system
SoC	state of charge
EMS	energy management strategy
EEMS	external energy maximization strategy
ECMS	equivalent consumption minimization strategy
SMCS	state machine control strategy
BES	bald eagle search algorithm
PSO	particle swarm optimization
EO	equilibrium optimizer
EUDC	Extra-Urban Driving Cycle
NEDC	New European Driving Cycle

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