electronics

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Energy Management Strategy of Fuel-Cell Backup Power Supply Systems Based on Whale Optimization Fuzzy Control

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Abstract: A backup power supply system can provide electrical energy for load in harsh environment without power grid, and plays a very important role in natural disaster rescue and military application. Compared with traditional energy sources, the proton-exchange membrane fuel cell has the advantages of good low temperature start-up performance, low noise, high efficiency and high power density, and no carbon emission, which gradually becomes the main energy source of the backup power supply system. This paper designs the backup power system topology of the "dual fuel cell and lithium battery" and researches energy management strategy based on fuzzy control (FC). Considering that it is difficult for the fuzzy controller to obtain the optimal membership function parameters according to working conditions, this paper aims to reduce the hydrogen consumption of the system, uses the whale optimization algorithm to optimize the membership function of the fuzzy controller, and proposes an energy management strategy based on whale optimization fuzzy control (WO-FC). The energy management strategies are verified and compared by simulations. The results show that the membership function of the optimized fuzzy controller based on WO-FC energy management strategy has changed greatly: The hydrogen consumption of the system obviously decreased compared with no optimization, and the overall efficiency of the fuel cell also significantly improved. To be more precise, the energy management strategy based on WO-FC reduces the hydrogen consumption of the system by 5.35% and improves the overall efficiency of the fuel cell by 1.56%.

Keywords: backup power supply; fuel cell; energy management; fuzzy control; whale optimization algorithm

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Citation: Cheng, Y.; Zhang, Y.; Chen, Q. Energy Management Strategy of Fuel-Cell Backup Power Supply Systems Based on Whale Optimization Fuzzy Control. *Electronics* **2022**, *11*, 2325. https://doi.org/10.3390/electronics11152325

Academic Editors: Angelo Accetta, Marcello Pucci, Giuseppe La Tona and Antonino Sferlazza

Received: 30 June 2022
Accepted: 22 July 2022
Published: 26 July 2022

1. Introduction

In recent years, power interruptions caused by failure of the power systems or natural disasters have occurred from time to time. A backup power has an important impact on natural disaster rescue, military operations, and industrial sectors and people's livelihood protection. It not only provides electric energy for lighting, medical rescue, and life support equipment in disaster areas, but also provides a guarantee for the reliable operation and uninterrupted power supply of various military communication and reconnaissance equipment in the suburban field and other environments.

At present, the energy sources commonly used in backup power supply system mainly include diesel generators and batteries. The diesel power generation backup power supply system is based on diesel such as fuel and generates electricity to the load through the diesel generator. However, the diesel generator not only has the disadvantage of generating loud noise in the process of power generation but also continuously produces toxic and harmful gases, causing environmental pollution [1]. While the battery backup power supply system has little environmental pollution, since the single battery pack energy density is low, it is necessary to improve the power of the system by increasing the number of battery packs; thus, the long backup time of the battery is also one of its unavoidable shortcomings. In recent years, the proton-exchange membrane fuel cells, as a high-efficiency power generation device, have been shown to convert chemical energy into electrical output and have higher energy density than a battery with the same power [2]. Proton-exchange membrane fuel cells are clean and pollution-free and have the advantages of fast startup and low noise [3–5]; hence, fuel cells are replacing diesel generators and batteries as the main energy source of backup power supply systems. However, due to the problems of soft output characteristics, slow dynamic response, and short lifespan of fuel cells, they are usually used in parallel with supercapacitors or lithium batteries to form a hybrid power system [6,7]. Reasonably distributing energy flow among energy sources of hybrid power systems has an important impact on giving full play to the advantages of each energy source and improving the fuel economy and overall performance of the system, which is also the core of energy-management strategy research [8].

In this regard, scholars and researchers have carried out relevant studies on energy management strategies of hybrid power systems. Generally speaking, energy management strategies can be divided into two categories: rule-based energy management strategies and optimization-based energy management strategies [9]. Rule-based energy management strategies usually rely on the experience and subjective ideas of designers or experts to design, which has the advantages of low implementation difficulty and low computation although it is difficult to obtain good results in the face of complex load conditions [10,11]. The optimization-based energy management strategy can optimize the energy management strategy according to established control objectives to obtain better control effects, but it is often difficult to realize and reduce the amount of calculation [12,13]. Compared with the traditional control algorithm, the fuzzy controller also has better performance in anti-interference, system parameter adaptation, and response speed [14,15]. It is very suitable for a fuel-cell emergency power system with nonlinear and strong time delay as designed in this article.

Since the birth of fuzzy logic control, through the application and development of many researchers, it has fully proved its advantages in solving complex system modeling and control problems. The well-known Mamdani-type fuzzy inference system [16] makes it possible to implement actual controllers based on language rules without the need for an accurate system model. Chen et al. [17] proposed a fuzzy control strategy of parameter adaptive tuning for fuel-cell hybrid power systems, which could maintain the battery SOC in the set state. Ming et al. [18] first formulated the rule-based algorithm, then proposed an energy-management strategy based on fuzzy control to improve it, and carried out simulation verification in three typical working conditions. Currently, some researchers adopted the control method based on fuzzy logic to improve the robustness of the control system. However, in the process of energy management strategy design based on fuzzy control, the design of membership functions and fuzzy control rules is usually based on expert knowledge and practical engineering experience and often has strong subjectivity. Therefore, the fuzzy control energy management strategy cannot achieve a good control effect in the operation of emergency power systems.

Based on the above, Sohani et al. [19] used a genetic algorithm to optimize the parameters of an energy management strategy based on fuzzy control in order to obtain the optimal distribution of fuel-cell hybrid electric vehicle energy flow. Currently, most of the research focuses on the fuel economy optimization of the powertrain by genetic algorithms. However, these control strategies ignore the impact of drastic power changes on the life of fuel cells. To solve this problem, Ahmadi et al. [20] adopted the method of introducing a penalty factor to affect the adaptation value. The iteration results not only optimized fuel economy but also optimized fuel-cell durability. In addition, Yin et al. [21] used a particle swarm optimization algorithm to optimize the fuzzy controller. However, these control strategies often have difficulty in parameter settings, requiring large amounts of calculation, and only aim at a single optimization objective in the optimization process, ignoring the influence of drastic power variation on the life of the fuel cell.

The main contribution of this paper is to design the fuel-cell backup power system structure of the "dual fuel cell + lithium battery". According to the characteristics of each energy source and the distribution principle of energy flow in the fuel-cell backup power supply system, an energy management strategy based on fuzzy control is designed. The whale optimization algorithm is a new intelligent optimization algorithm proposed in recent years; it is more competitive than other optimization algorithms in terms of convergence speed, implementation difficulty, and optimization accuracy. Therefore, the whale optimization algorithm is used to optimize the membership function of fuzzy controllers globally in order to realize the simultaneous optimization of hydrogen consumption and fuel-cell output power fluctuation.

This paper is organized as follows: Section 2 designs the topology of fuel-cell backup power supply systems. In Section 3, the energy management strategy based on fuzzy control is designed. Section 4 introduces the optimization process of membership function of fuzzy controllers by the whale optimization algorithm and designs an energy management strategy based on whale optimization fuzzy control. Finally, the simulation results and conclusion analysis of energy-management strategies are presented in Section 5.

2. System Design

Figure 1 shows the topology structure of the fuel-cell backup power supply system.

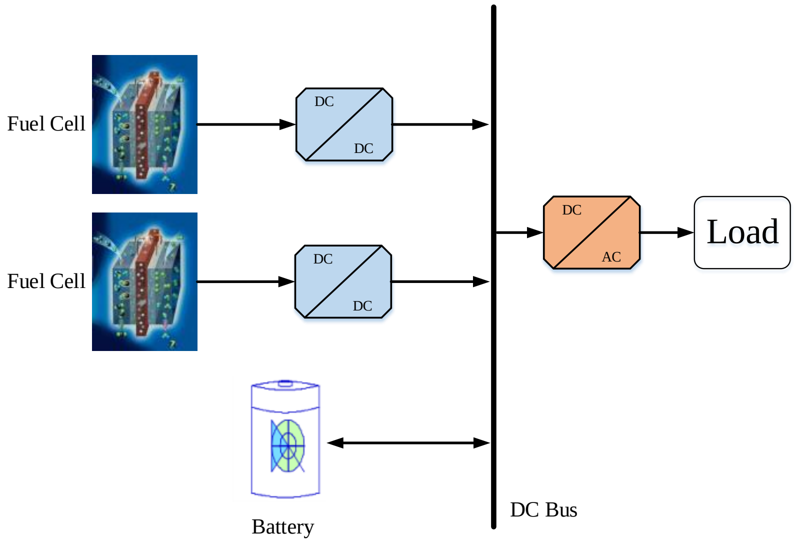

Figure 1. Topology structure of the fuel-cell backup power supply system.

During the operation of the system, due to the hysteresis of the output of the fuel cell itself, the system uses the lithium battery as the auxiliary energy source. Before the load power suddenly changes and the fuel-cell output becomes stable, the lithium battery mainly supplies the load. Fuel cells are employed upon load increasing. Therefore, the lithium battery and the fuel cell are connected in parallel on the bus bar, and an inverter is connected to the rear stage of the bus bar to provide electrical energy for the load.

In order to further improve the reliability of the fuel-cell backup power supply system during operation, this paper adopts the main energy source structure of dual-fuel cells, which are connected to the DC bus through a one-way Buck DC/DC converter and controlled by their respective independent controllers. This structure can still work normally in the case of a failure in a single reactor in low load demands and can improve the output power fluctuation of a single reactor. The energy management controller completes the power distribution between the fuel cell and the lithium battery by controlling the input current of the DC/DC converter according to the load demand.

3. Fuzzy Controller Design

The fuzzy controller usually consists of five parts: fuzzification, rule base, database, inference engine, and defuzzification [22], as shown in Figure 2.

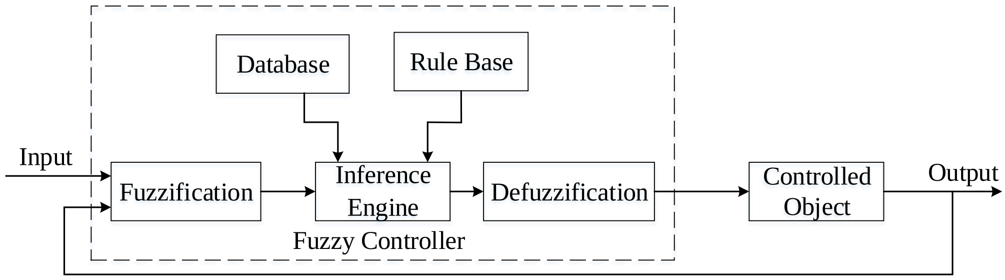

Figure 2. Composition of fuzzy controller.

The design of the fuzzy controller in this paper adopts the Mamdani structure with dual-input and single-output. The load demand power, P_{load}, and the lithium battery SOC are taken as the input variables of the fuzzy controller; the total output power, P_{fc}, of the two fuel-cell modules is taken as the output variable; the output power of two fuel-cell modules is evenly distributed.

Considering the large amount of calculation for some types of membership function and the requirements of real-time controllers and easy parameter adjustment in fuel-cell backup power supply systems, triangle and trapezoid functions are more suitable as the research objects of membership function design. In this paper, the power range of load requirement is set as 0–8 kW, and the health range of lithium battery SOC is set as 30–80%. After scaling the three variables, the domains of P_{load}, lithium battery SOC, and fuel-cell module P_{fc} are $[-4, 4]$, $[-2, 2]$, and $[-4, 4]$, respectively.

The fuzzy subsets of the three variables are divided into VL, L, M, H, VH, which are very small, small, medium, large, and very large, respectively. The fuzzy control rules are shown in Table 1. The output power of the fuel cell should be higher when the load demand is high and the lithium battery SOC is low, while the output power of the lithium battery should be appropriately increased when the load demand is low and the lithium battery SOC is high.

Table 1. Fuzzy control rules.

P_{fc}		SOC				
		VL	**L**	**M**	**H**	**VH**
P_{load}	VL	M	M	L	VL	VL
	L	M	M	M	L	VL
	M	H	M	M	M	L
	H	H	H	M	M	M
	VH	VH	H	H	H	M

4. Fuzzy Controller Design Based on Whale Optimization Algorithm

4.1. Whale Optimization Algorithm

As a new intelligent optimization algorithm proposed in recent years, the whale optimization algorithm is more competitive than similar optimization algorithms in terms of convergence speed, implementation difficulty, and optimization accuracy [23]. Therefore, the whale optimization algorithm is used to optimize the membership function of the fuzzy controller in the further study of this paper.

The optimization process of the whale optimization algorithm mainly includes three stages: the prey encirclement stage, the bubble net attack stage, and the prey search stage.

The equations for updating the position in the prey encirclement stage are as follows:

$$\vec{D} = \left| \vec{C} \cdot \vec{W}^*(t) - \vec{W}(t) \right| \tag{1}$$

$$\vec{W}(t+1) = \vec{W}^*(t) - \vec{A} \cdot \vec{D} \tag{2}$$

where $\vec{W}(t)$ is the position of whales in the population at the current moment; $\vec{W}^*(t)$ is the optimal position reached by the population so far; t is the number of iterations currently experienced; and $\vec{A}$ and $\vec{C}$ are the vectors of coefficients, which can be adjusted to make the whales in the population gradually approach the whales in the optimal position at the current time.

The calculation of $\vec{A}$ and $\vec{C}$ are as follows:

$$\vec{A} = 2\vec{a} \cdot \vec{r} - \vec{a} \tag{3}$$

$$\vec{C} = 2\vec{r} \tag{4}$$

where $\vec{r}$ is a random vector in [0, 1] and $\vec{a}$ decreases linearly from 2 to 0 as the number of iterations increases.

In the bubble net attack stage, the hunting methods of humpback whales are divided into two types: the shrinking and wrapping mechanism and the spiral approximation mechanism. During this stage, whales will encircle their prey in a spiral path and continuously shrink the encirclement. Each individual whale in the population has a 50% chance to update its position through the shrinking and wrapping mechanism or the spiral approximation mechanism. The position update of the shrinking and wrapping mechanism is completed by Equation (2), and the position update of the spiral approximation mechanism is as follows:

$$\vec{D'} = \left|\vec{W}^*(t) - \vec{W}(t)\right| \tag{5}$$

$$\vec{W}(t+1) = \vec{D'} \cdot e^{bl} \cdot \cos(2\pi l) + \vec{W}^*(t) \tag{6}$$

where $\vec{D'}$ is the distance between the current position of whales in the population and the optimal position reached by the population so far; b is the constant coefficient, which determines the logarithmic spiral shape; and l is the random number between $[-1, 1]$.

The equations for updating the position in the prey search stage are as follows:

$$\vec{D} = \left|\vec{C} \cdot \vec{W}_{rand} - \vec{W}\right| \tag{7}$$

$$\vec{W}(t+1) = \vec{W}_{rand} - \vec{A} \cdot \vec{D} \tag{8}$$

where $\vec{W}_{rand}$ is the position of a whale randomly selected from the population at the current moment and taken as the target for other whales to approach.

Therefore, the whale optimization algorithm selects the position update equation to update the position of the whales in the population according to the value of the random number, p, and the coefficient vector, $\left|\vec{A}\right|$:

$$\vec{W}(t+1) = \begin{cases} \vec{W}^*(t) - \vec{A} \cdot \vec{D} & p < 0.5, \left|\vec{A}\right| \leq 1 \\ \vec{W}_{rand}(t) - \vec{A} \cdot \vec{D} & p < 0.5, \left|\vec{A}\right| > 1 \\ \vec{D'} \cdot e^{bl} \cdot \cos(2\pi l) + \vec{W}^*(t) & p \geq 0.5 \end{cases} \tag{9}$$

where p is the random number between $[-1, 1]$.

In this paper, the position of the whale is encoded by the parameter to be optimized in the membership function of the fuzzy controller. The initial position of each whale is randomly generated within the range of its parameter variation, and the fitness of each whale and the three-stages mathematical model of algorithm are calculated for iterative updates of whale positions according to the optimization objective function. When the algorithm reaches the termination condition, the whale in the optimal position at that time is the global optimal solution, and the encoding of its position is the optimal parameter of the membership function.

4.2. Optimization Objective Function

In the fuel-cell backup power supply system designed in this paper, the energy source consists of two fuel-cell modules and an auxiliary battery. In order to improve the economy of the system, the main goal of this paper's optimization of the energy management strategy is to reduce the hydrogen consumption of the fuel-cell module. The equation for calculating the hydrogen consumption of the system fuel cell is shown in (10):

$$M_{fc} = \frac{N}{E_{LH}} \int \frac{p_{fcs}}{\eta_{fc}(p_{fcs})} dt \tag{10}$$

where M_{fc} is the total hydrogen consumption of the fuel-cell module of the system; E_{LH} is the low calorific value of hydrogen, which is 1.2×10^5 J/g; η_{fc} is the efficiency of the fuel cell using hydrogen to generate electricity; P_{fcs} is the output power of a single fuel cell module; and N is the number of fuel-cell modules, which is set at 2.

The relationship curve between the efficiency of fuel cells using hydrogen to generate electricity and its output power, P_{fcs}, is shown in Figure 3.

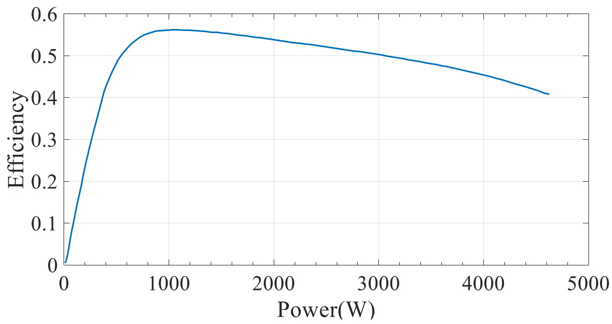

Figure 3. Relationship curve between the efficiency of fuel cells and output power.

After fitting the efficiency curve in Matlab, the mathematical model of the efficiency of the fuel cell using hydrogen to generate electricity and its output power is shown as follows.

$$\eta_{fc} = \begin{cases} a_1 P_{fcs}{}^4 + a_2 P_{fcs}{}^3 + a_3 P_{fcs}{}^2 + a_4 P_{fcs} + a_5 & P_{fcs} \le 1000 \\ b_1 P_{fcs}{}^5 + b_2 P_{fcs}{}^4 + b_3 P_{fcs}{}^3 + b_4 P_{fcs}{}^2 + b_5 P_{fcs} + b_6 & P_{fcs} > 1000 \end{cases} \tag{11}$$

Specific parameters are shown in Table 2.

Table 2. Efficiency parameters of fuel cell.

Parameter	Value
α_1	9.283×10^{-13}
α_2	-1.551×10^{-9}
α_3	-1.415×10^{-7}
α_4	1.343×10^{-3}
α_5	-0.0175
b_1	5.218×10^{-19}
b_2	-8.524×10^{-15}
b_3	5.115×10^{-11}
b_4	1.468×10^{-7}
b_5	1.7×10^{-4}
b_6	0.4961

When designing the optimization objective function, in order to protect the fuel-cell and prolong its service life, the output power should be kept stable and the fluctuation should be reduced as much as possible [24]. The output power fluctuation of the fuel-cell module should be increased as a secondary optimization objective.

$$\Delta P_{fcs}(k) = P_{fcs}(k) - P_{fcs}(k-1) \tag{12}$$

$$\Delta P_{fcs,\min} \leq \Delta P_{fcs} \leq \Delta P_{fcs,\max} \tag{13}$$

where $\Delta P_{fcs}(k)$ is the fluctuation of fuel-cell module output power at time k, and $\Delta P_{fcs,\min}$ and $\Delta P_{fcs,\max}$ are the minimum and maximum value of transient fluctuation of fuel-cell output power per second, respectively.

Therefore, the optimization objective function, J, designed in this paper is as follows:

$$J = \lambda_1 M_{fc} + \lambda_2 \Delta P_{fcs}^2 \tag{14}$$

where λ_1 and λ_2 are the weight value; ΔP_{fcs} is the fluctuation of fuel-cell module output power; M_{fc} is the total hydrogen consumption of the system fuel-cell module.

At the same time, in order to avoid the phenomenon of overcharge and overdischarge of the lithium battery and so that the SOC can always be within a healthy range, the fluctuation range of the SOC of the lithium battery should also be considered as a secondary optimization target. The calculation equations for SOC fluctuation amount and constraint conditions of lithium battery SOC are as follows:

$$SOC = \frac{Q_0 - \int_0^t i(t)dt}{Q_{\max}} \tag{15}$$

$$\Delta SOC(k) = SOC(k) - SOC(k-1) \tag{16}$$

$$SOC_{\min} \leq SOC(k) \leq SOC_{\max} \tag{17}$$

where Q_0 and $Q_{\max}$ are the initial capacity and maximum capacity of lithium battery, respectively; i is the current of the lithium battery; $\Delta SOC(k)$ is the fluctuation of SOC at moment k; and $SOC_{\min}$ and $SOC_{\max}$ are, respectively, the lower limit and upper limit of the health range of auxiliary battery SOC. This paper takes 30% and 80%, respectively.

4.3. Optimization Solution

In this paper, the population size of whales is set at 30, the dimension of the solution space is 8, and the maximum number of iterations is 100. The simulation model of the fuel-cell backup power supply system is built in the Matlab/Simulink environment by combining the whale optimization algorithm with the system model simulation to solve the optimization objective function. The solution parameters are shown in Table 3.

Table 3. Solution parameters.

Parameter	Value
Size of population	30
Maximum number of iterations	100
Dimension of solution space	8
Hydrogen low calorific value E_{LH}	1.2×10^5 J/g
Maximum hydrogen utilization efficiency $\eta_{fc.\max}$	55%
Upper of SOC Health range $SOC_{\max}$	80%
Lower of Health range cap $SOC_{\min}$	30%
Lithium battery initial SOC	60%
Weight value $\lambda_1,\ \lambda_2$	8, 2

As observed from Figure 4, the objective function value tends to converge after about 28 iterations. At this point, a set of optimal membership functions is obtained. This paper adopts the offline optimization method. It can be seen from the optimization process that the calculation speed and convergence speed meets the requirements.

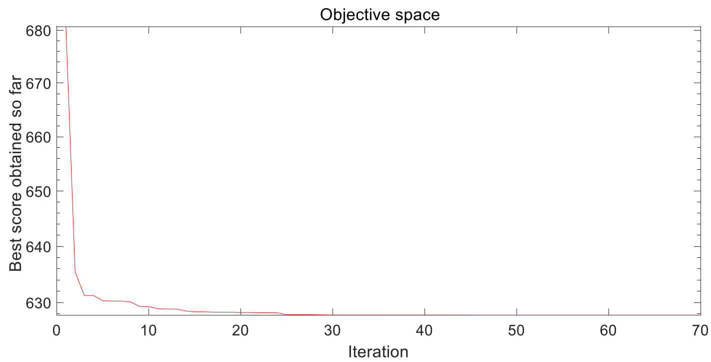

Figure 4. Iterative convergence curve.

Figures 5–7, show the membership function of optimized load demand power P_{load}, lithium battery SOC, and total output power P_{fc} of the fuel-cell module, respectively.

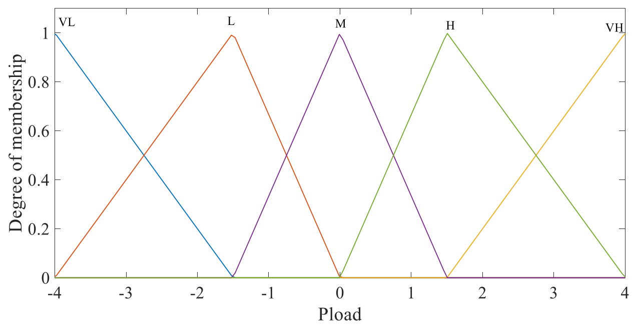

Figure 5. Optimized membership function of load demand power.

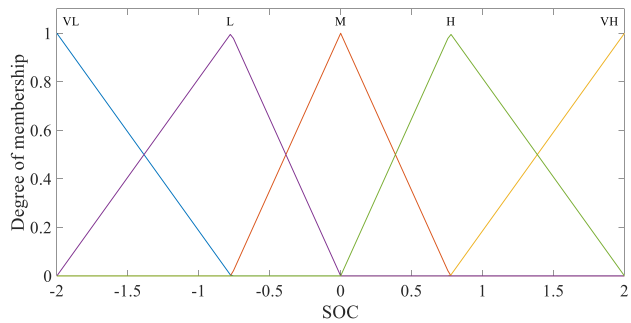

Figure 6. Optimized membership function of lithium battery SOC.

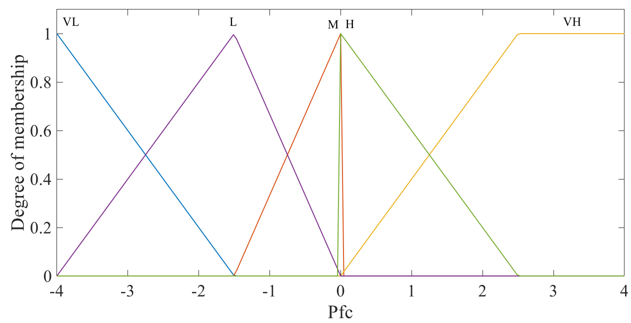

Figure 7. Optimized membership function of total output power of fuel-cell module.

5. Simulation and Analysis of Results

In order to verify the effectiveness of the energy management strategy proposed in this paper, a simulation model of the fuel-cell backup power system was established. The rated power of single fuel-cell module was 4.5 kW, the capacity of lithium battery was 2 kWh, the rated voltage was 48 V, and the simulation step size Ts was set as 0.1 s. Figure 8 shows a set of load power requirements according to actual working conditions, which is used for the optimization and simulation verification of the fuzzy controller.

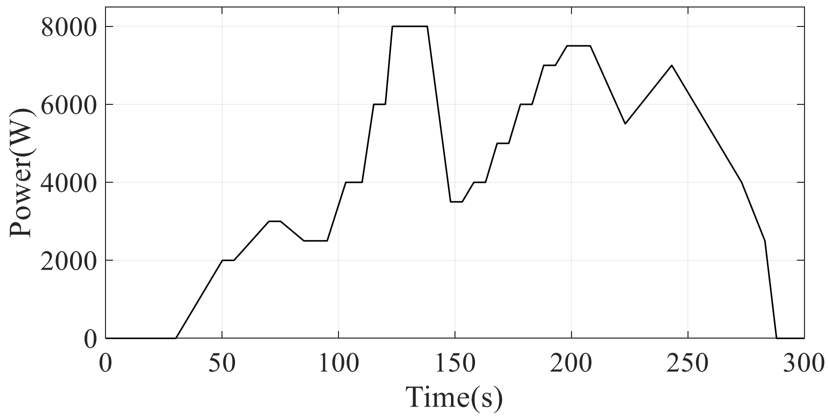

Figure 8. Load power requirements.

The energy management strategies before and after optimization are substituted into the simulation model for verification. Figure 9 shows the power curve of the energy management strategy based on FC, and Figure 10 shows the curve of the energy management strategy based on WO-FC. As observed from the two figures, the output power curve of a single fuel cell of the energy management strategy based on WO-FC proposed in this paper decreases slightly and is relatively gentle compared with that before optimization. By comparing the efficiency curve in Figure 3, it can be seen that the efficiency of a fuel cell using hydrogen for power generation is the highest at about 1 kW and then efficiency decreases gradually with the increase in output power. According to (11), the real-time efficiency curve of fuel cells based the two energy management strategies shown in Figure 11 is obtained. Figure 11 shows that the real-time hydrogen utilization power generation efficiency of fuel cells is significantly higher for the WO-FC energy management strategy, which indicates that the energy-management strategy based on WO-FC can effectively reduce the hydrogen consumption of the system and improve system efficiency.

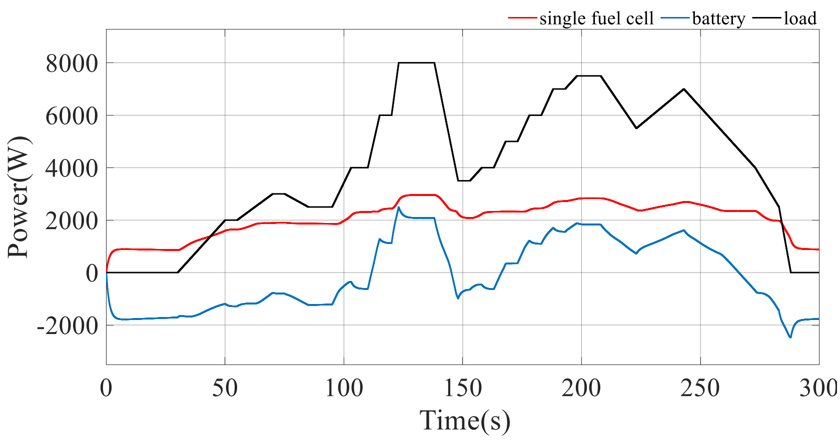

Figure 9. Power curve of the energy management strategy based on FC.

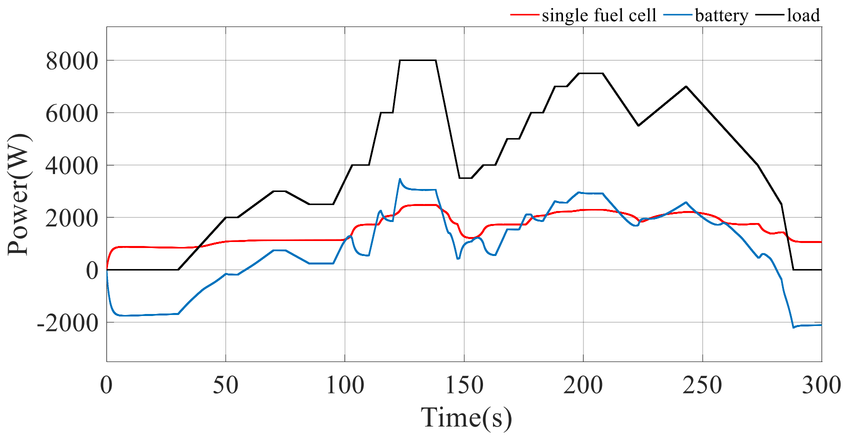

Figure 10. Curve of the energy management strategy based on WO-FC.

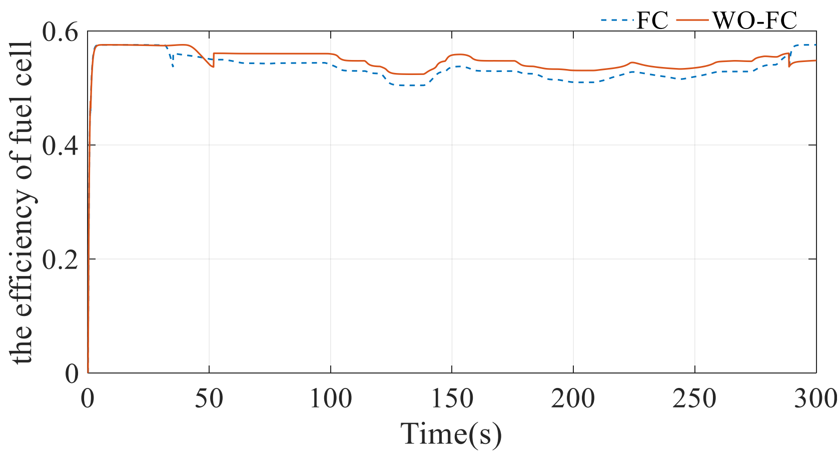

Figure 11. Real-time efficiency curve of fuel cell based on the two energy management strategies.

Figure 12 shows the SOC curves of lithium batteries based on the two energy management strategies. It can be seen from the Figure that based the two energy-management strategies, lithium battery SOC is always within the healthy range set in this paper, and that, based on the WO-FC energy management strategy, the final value of lithium battery SOC is 56.70%.

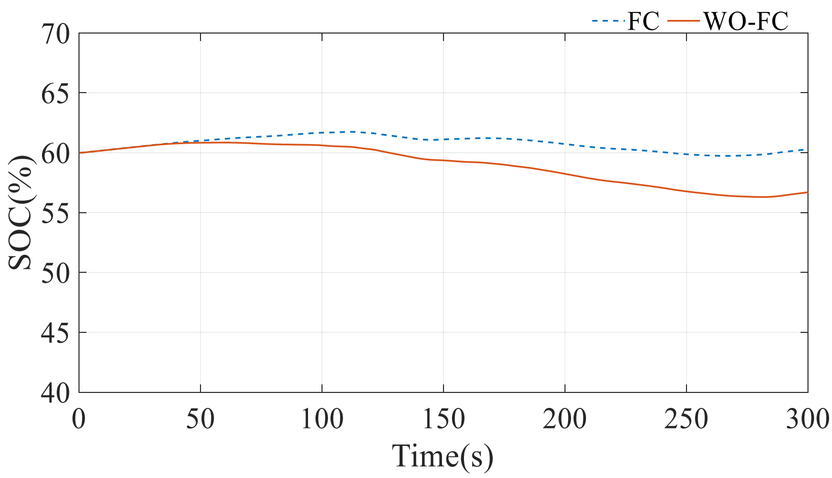

Figure 12. SOC curves of lithium batteries based on two energy management strategies.

In order to quantitatively analyze the advantages of system hydrogen consumption based on the WO-FC energy-management strategy, the optimization effect of hydrogen consumption of fuel-cell backup power supply systems is defined as follows:

$$\mu = (1 - M_{WO\text{-}FC}/M_{FC}) \times 100\% \tag{18}$$

where $M_{WO\text{-}FC}$ is the hydrogen consumption of the system based on the WO-FC energy management strategy; and M_{FC} is the hydrogen consumption of the system based on the FC energy management strategy.

The overall efficiency of fuel cells [25] is defined as follows:

$$\eta_{all,P_{fc}} = \int P_{fc} dt/(ME_{LH}) \times 100\% \tag{19}$$

where M is the total hydrogen consumption of the fuel-cell module in its entire working condition.

The hydrogen consumption of the system based on the two energy management strategies are shown in Table 4.

Table 4. Hydrogen consumption of the system.

Energy Management Strategy	SOC Initial Value	SOC Final Value	Hydrogen Consumption of the System	Overall Efficiency of Fuel Cells
FC	60%	60.29%	19.25 g	52.68%
WO-FC	60%	56.70%	18.22 g	54.24%

As observed from Table 4, compared with the FC energy-management strategy before optimization, the WO-FC energy-management strategy reduces the hydrogen consumption of the system by 5.35% and the overall efficiency of fuel cell increased by 1.56%.

6. Conclusions

This paper proposes a method to optimize the membership function in the fuzzy controller by applying the whale optimization algorithm and verifies the effectiveness of the energy management strategy before and after optimization by using the simulation model of the fuel-cell backup power supply system. An optimization objective function was designed to reduce hydrogen consumption, and the optimal membership function parameters were obtained using a joint solution with the simulation model. Finally, the simulation results verify that, compared with the FC energy management strategy, the WO-FC energy management strategy reduces the hydrogen consumption of the system by 5.35%, and the overall real-time efficiency of the fuel cell significantly improved.

Author Contributions: Conceptualization, Y.Z.; validation, Y.C. and Y.Z.; data curation, Y.C.; writing—original draft preparation, Y.C.; writing—review and editing, Y.Z. and Y.C.; supervision, Q.C. All authors have read and agreed to the published version of the manuscript.

Funding: National Natural Science Foundation of China under grant 62173264.

Acknowledgments: The authors would like to express gratitude to all those who aided them in the writing of this paper.

Conflicts of Interest: The authors declare no conflict of interest.

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