Research Article

Optimization of Hybrid Energy Storage System Control Strategy for Pure Electric Vehicle Based on Typical Driving Cycle

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1.Introduction

In recent years, new energy vehicles have become the main development direction of the automobile industry. Compared with fuel vehicles, pure electric vehicles have the characteristics of energy saving and environmental protection without exhaust pollution. However, owing to the influence of the battery material, power supply form, power management strategy, and driving environment, pure electric vehicles (EVs) have defects such as short endurance mileage and poor energy consumption stability. Among them, whether the energy management and control system of a hybrid energy storage system (HESS) can provide the best energy distribution strategy according to changes in the working conditions has become one of the hot spots in current research on the energy management and control of EVs. By improving the power management and control system of electric vehicles, the stability of the management strategy and endurance mileage of EVs can be improved.

To improve the energy control efficiency of EVs and emphasize real-time optimization, domestic and overseas scholars have conducted significant amounts of research on energy control strategies and predictive control. Some scholars optimized the working efficiency of the HESS. In [1, 2], a new hybrid battery/ultracapacitor energy storage system for electric vehicles (including electric vehicles, hybrid vehicles, and plug-in hybrid vehicles) was proposed. This system uses a smaller DC/DC converter as a controlled energy pump to keep the voltage of the ultracapacitor higher than that of the battery under urban driving conditions. In [3], a modulator replaces the DC/DC converter for
connections, which solves the problem of large voltage changes caused by ultracapacitor power transmission. Thus, the drive performance of the motor is not disturbed.

Research on energy management strategies can optimize the energy efficiency of the entire vehicle without changing the basic components and framework of the HESS. In [4], an optimization framework was proposed to calculate the suboptimal current of the hybrid system in an EV to control the current and minimize the working current and fluctuation of the battery in the EV. In [5–8], by combining a battery and ultracapacitor, an energy control strategy with fuzzy control strategy as the core was proposed to improve the fuel economy and durability of energy system components while maintaining the vehicle power performance. In [9, 10], a real-time optimal energy management strategy (EMS) was proposed for a plug-in hybrid bus based on the minimum equivalent fuel consumption strategy and considering the frequent starting of a low-speed engine. In [11, 12], the energy management of a hybrid power system was analyzed. The energy flow of different energy sources was managed separately by combining fuzzy logic control and shape control. In [13], the online predictive control strategy of a series and parallel plug-in hybrid EV was studied. A new dual-loop online intelligent planning (DOIP) method for speed prediction and energy flow control was proposed, and a depth fuzzy predictor was established to realize directional speed prediction. The optimal control behavior was determined by learning the vehicle speed and acceleration.

There are also some scholars who use algorithms to optimize research. Reference [14] has proposed an adaptive power distribution algorithm. The parameters of the algorithm were optimized by combining self-organizing mapping and particle swarm optimization (PSO) to alleviate the peak demand and short charge and discharge period of the battery. In [15, 16], the focus is on the k-means clustering algorithm. Reference [15] focuses on the study of the driving cycle of cars in Tehran and its suburbs. By collecting the situation of vehicles running in actual traffic, the calculation is based on the definition of “micro-travel.” Two driving functions, “average speed” and “idle time percentage,” are calculated. The micro-trips are then clustered into four groups in driving feature space using the k-means clustering method. The focus of [16] is the application of driving condition recognition in hybrid electric vehicle intelligent control. For this purpose, driving features are identified and used for driving segment clustering, using the k-means clustering algorithm. Many combinations of driving features and different numbers of clusters are evaluated, in order to achieve the best traffic condition recognition results. References [17, 18] also record the vehicle data and driving data under the actual traffic conditions, analyze the driving end, and study the influence of driving characteristics on the fuel consumption and exhaust emissions through the driving segment simulation. The results of [17] show that the velocity-dependent driving features such as “energy,” “mean of velocity,” “displacement,” and “maximum velocity” are more effective in vehicle exhaust emissions and fuel economy. The results of [18] show that “energy” and “percentage of free time” are two driving characteristics to drive segmented clustering. Driving segment clustering can be used in driving cycle development, intelligent hybrid vehicle control and so on.

In the current study, most of the control strategies of EVs are optimized in one algorithm. Based on the above research, this paper uses fuzzy control strategy as an EMS with the composite power supply form of a combined battery and ultracapacitor. Reducing the total energy consumption is the optimization goal, and GA and PSO are used to carry out learning optimization for the fuzzy control strategy in MATLAB/Advisor in the UDDS, NEDC, and ChinaCity driving cycles. In the same simulation environment, the theoretical minimum energy consumption of HESS is calculated by DP algorithm. An experimental analysis is carried out to compare the battery current output performance and the total energy consumption parameters of the energy system and to evaluate the optimization effect of the algorithm.

2. System Description and Methodology

2.1. Modeling of HESS. There are three common types of composite power supply structure: passive, semiactive, and active. The semiactive structure has two types: battery end load and capacitor end load. The main feature of the passive hybrid energy system is that the battery and the ultracapacitor are separately connected in parallel and series. The composite power supply with an active structure has two DC/DC converters that are connected in series with batteries and capacitors. The two DC/DC converters are integrated and connected in series. Both of these forms can flexibly adjust the distribution of the energy output, but the energy system structure is complex and the actual application cost is high [19].

Therefore, in this study, the battery terminal load structure of a semiactive energy system is selected. Its topology is shown in Figure 1. The battery and capacitor are isolated by a DC/DC converter. The battery acts as the main power supply, and the capacitor is the auxiliary power supply. The energy system distribution of the battery and capacitor can be realized through high and low voltage conversions of the voltage. Compared with the battery end load, the ultracapacitor is used as the main power supply in the form of the capacitor end load. Owing to the low capacity of the capacitor energy, the battery needs to participate in driving, and all current flowing through the battery needs to pass through the DC/DC converter. This makes the battery work with low efficiency and high energy consumption.

2.2. Modeling of Battery. Battery modeling is a significant task within battery technology development and is vital in applications. For example, EV range prediction is only possible through the application of advanced battery modeling and estimation techniques to determine current
and predict remaining endurance. In addition, battery modeling is essential for safe charging and discharging, optimal utilization of batteries, fast charging, and other applications [20].

A battery simulation model verifies the correctness of the model parameter settings in a simulation. Generally, the input is the current, and the output is the terminal voltage. Because the current, power, temperature, state of charge (SOC), and other parameters have nonlinear effects on the battery characteristics, considering all factors in modeling makes the simulation calculation too large and difficult to control.

Equivalent circuit models of a battery include the Rint model, the Thévenin model, and the second-order reserve capacity (RC) model. The Rint model is the equivalent circuit model of internal resistance, which regards the battery as a series model of the ideal voltage source and resistance. In this model, it is easy to set the parameters and run a simulation, but the accuracy is low. The Thévenin model is a first-order RC model and contains a voltage source and an RC parallel circuit. The model fully considers the relationship between the electromotive force and SOC and the dynamic process of the battery. It can accurately simulate the battery charging and discharging process, but it does not consider the open-circuit voltage changes caused by the current accumulation, so it is not suitable for long-time simulations. The second-order RC model adds a group of RC circuits on the basis of the Thévenin model. In the model, the variable voltage source connects the resistance and two RC circuits. This can provide better consideration to the transient and steady-state characteristics of the battery but does not consider the influence of the temperature and battery self-discharge [21, 22].

This paper compares the optimization effects of different algorithms and does not require a high-precision simulation, so the more universal Rint model is selected for modeling. Figure 2 shows the battery equivalent circuit model, and the mathematical model is described as follows:

\[
\begin{align*}
Q_b &= n_{b1}n_{b2}Q_{bc}, \\
R_b &= \frac{n_{b1}R_{bc}}{n_{b2}}, \\
U_b &= n_{b1}U_{bc}, \\
\frac{d\text{SOC}_b}{dt} &= \frac{U_b - \sqrt{U_b^2 - 4R_bP_m}}{2R_bQ_b}, \\
P_b &= -\frac{d\text{SOC}_b}{dt}U_bQ_b,
\end{align*}
\]

where \(Q_b\), \(R_b\), and \(U_b\), respectively, represent the capacity, internal resistance, and terminal voltage of the battery pack; \(Q_{bc}\), \(R_{bc}\), and \(U_{bc}\), respectively, represent the capacity, internal resistance, and terminal voltage of the battery cell; \(n_{b1}\) and \(n_{b2}\), respectively, represent the number of series and parallel modules in the battery pack; and \(P_b\) is the power density of the battery.

2.3. Modeling of Ultracapacitor. An ultracapacitor is a type of electrochemical element that stores energy by virtue of physical characteristics. Unlike a battery with a large capacity, the ultracapacitor has a higher energy density, higher charge and discharge power, and longer cycle life. It is suitable to use for power transport in the start and stop stages, active suspension systems, and rapid acceleration stage. In recent years, ultracapacitors have been widely used in high-power energy storage systems of vehicles, ships, and aerospace projects [23–25].

The RC internal-resistance model, which is common and easy to implement, is also selected to describe the ultracapacitor. The model is generally composed of a series resistance, parallel resistance, and ideal capacitor. The equivalent circuit model is shown in Figure 3.
According to the operation conditions and power demand of the EV, the demand power of the EV is $P_{\text{req}}$ and the output power of the HESS ($P_{\text{hy}}$) is composed of the battery output power ($P_{\text{bat}}$), ultracapacitor output power ($P_{\text{uc}}$), and system loss power ($P_{\text{e}}$). The mathematical model can be written as

$$P_{\text{hy}} = P_{\text{bat}} + P_{\text{uc}} + P_{\text{e}},$$

$$P_{\text{req}} = P_{\text{hy}} - P_{\text{e}}.$$  (3)

Since the energy loss of the system is low and difficult to calculate and the loss is ignored in this study, the output power of the HESS can be calculated as

$$P_{\text{req}} = P_{\text{hy}} = P_{\text{bat}} + P_{\text{uc}}.$$  (4)

In the operating process of the vehicle, the output power of the battery pack and ultracapacitor is mainly determined by the SOC of the battery/ultracapacitor and the system demand power. Therefore, energy distribution factors ($K_{\text{bat}}$ and $K_{\text{uc}}$) are proposed to describe the power output of the battery and capacitor, shown as follows:

$$\begin{align*}
K_{\text{bat}} &= \frac{P_{\text{bat}}}{P_{\text{req}}}, \\
K_{\text{uc}} &= \frac{P_{\text{uc}}}{P_{\text{req}}}, \\
K_{\text{bat}} + K_{\text{uc}} &= 1.
\end{align*}$$  (5)

Fuzzy control is widely used in various fields. For the management of vehicle energy system, the control method can set different control variables and controlled objects and improve the fuel economy and emissions of the whole vehicle by establishing different fuzzy rules [27–29]. Based on the structure and power requirement of the energy system, the structure of fuzzy control logic is shown in Figure 5. A fuzzy logic control strategy is used to manage the energy transport, and two fuzzy control rules that represent the output power for driving and recovery power for braking are established. The fuzzy logic rule for the output driving energy adopts the form of three inputs and one output. The three inputs are the vehicle demand power ($P_{\text{req}}$) and the SOC of the battery (SOC$_{\text{bat}}$) and ultracapacitor (SOC$_{\text{uc}}$). The output is the energy distribution factor ($K_{\text{uc}}$). The fuzzy logic rule of braking energy recovery adopts the form of two inputs and one output. The two inputs are the SOCs of the battery (SOC$_{\text{bat}}$) and ultracapacitor (SOC$_{\text{uc}}$), and the output is the energy distribution factor ($K_{\text{uc}}$).

The construction form can avoid the frequency of high current output from the battery as much as possible on the premise that the power performance of the vehicle is satisfied. When there is a high energy demand, the ultracapacitor must have enough energy output power. When carrying out braking energy recovery, the ultracapacitor is used for energy recovery.

The Expert Experience Method is used to determine the membership function, and the Gauss, Z, S, and Triangle functions are selected as the membership functions to establish the fuzzy control rules of the HESS. The surface view of fuzzy rules is shown in Figure 6.
3.2. Algorithm Optimization. In order to use the algorithm for optimization, it is necessary to transform the specific problem into a mathematical model and establish the mapping relationship between the value space and coding; that is, the coding is used to represent the problem [30]. Because there are 27 membership functions in the fuzzy controller in this paper, the Gauss, Z, and S membership functions need only two variables to determine their
position and shape, while the Triangle function needs three variables to determine the position and shape of the function. Therefore, 65 parameters are needed to express the value space, as follows:

\[ X = \left( x_1^1, x_1^2, \ldots, x_{16}^1, x_{16}^2, x_{17}^1, x_{17}^2, \ldots, x_{27}^1, x_{27}^2, x_{27}^3 \right). \]  

(6)

The algorithm is used for optimization, and the mathematical model of the objective function is described as

\[ \min y = f(x). \]  

(7)

The energy consumption per unit mileage is set as the evaluation standard for the algorithm. It is shown as

\[ f(x) = \text{fitness} = \frac{\text{energy}}{\text{distance}}. \]  

(8)

The energy consumption of the HESS needs to consider the consumption of various components including the battery loss, supercapacitor loss, DC/DC converter loss, line loss, and motor loss in which the battery, capacitor, and DC/DC converter are the main consumption objects. Other losses are ignored. The mathematical model is shown as follows:

\[
\begin{align*}
\text{energy} &= P_{\text{bat}} + P_{uc} + E_{\text{bat}}^l + E_{uc}^l + E_{dc}^l, \\
E_{\text{bat}}^l &= I_{\text{bat}}^l(t)R, \\
E_{uc}^l &= I_{uc}^l(t)R_{uc}, \\
E_{dc}^l &= I_{in}^l(t)(1 - \eta_{dc}).
\end{align*}
\]

(9)

where \( P_{\text{bat}} \) and \( P_{uc} \) are the output power of the battery pack and the ultracapacitor, respectively; \( E_{\text{bat}}^l \), \( E_{uc}^l \), and \( E_{dc}^l \) are the loss of the battery pack, ultracapacitor, and DC/DC converter, respectively; \( I_{\text{bat}} \) and \( I_{uc} \) are the working current of the battery pack and the ultracapacitor, respectively; and \( \eta_{in} \) is the input current of the DC/DC converter.

To sum up, the algorithm optimizes the objective function shown as follows:

\[ \text{fitness} = \frac{P_{\text{bat}} + P_{uc}}{\text{distance}}. \]  

(10)

3.2.1. Genetic Algorithm Optimization. A genetic algorithm (GA) simulates the evolution phenomenon of the Darwinian theory of survival of the fittest in nature and uses the process of survival of the fittest and continuous genetic optimization in the process of evolution to solve the problem and find the optimal solution. All solutions are encoded, and the range of the solution is constantly close to the optimal solution through generations of genetic operations to solve the problem. Based on the evolutionary characteristics of the GA, the inherent properties of the problem are not needed in the process of searching the solution. The ergodicity of the individual enables the algorithm to effectively carry out a global search in the sense of probability, and has better identification accuracy for the entire world [31, 32]. The process of the GA is shown in Figure 7.

First, the solution to the specific problem is encoded, and the set of corresponding potential solutions is the initial population. Suppose that there are \( n \) individuals in an initial population, and the corresponding chromosomes and fitness are shown as

\[
\text{chrom} = \begin{bmatrix} x_1^1 & x_2^1 \\ x_1^2 & x_2^2 \\ \vdots & \vdots \\ x_1^n & x_2^n \end{bmatrix}, \quad \text{fitness} = [f_1, f_2, f_3, \ldots, f_n].
\]

(11)

Then, according to the specific problem, different strategies are used to evaluate the fitness of individuals, and the offspring is selected according to the fitness. Individuals with high fitness are more likely to be selected. New populations are generated through cross recombination and mutation. When they are inherited from the selected algebra or meet the fitness requirements, the individuals with the highest fitness output from the current population are taken as the optimal solution.

In this paper, the control strategy is optimized based on the GA. The steps of building the GA-Fuzzy Control are as follows:

1. Initialization algorithm: set the evolution algebra to 80, number of variables to 65, recombination probability to 0.5, mutation probability to 0.001, and generation gap to 0.95
(2) Initialization population: 65 individuals are randomly generated within the target range as the initial population

(3) Calculate fitness: calculate individual fitness according to the fitness function

(4) Judgment condition: whether the highest fitness of the individual meets the requirements, or whether the evolutionary algebra is terminated

(5) Update the population: select, cross over, and mutate the population to generate a new population, and return to the judgment conditions to continue the evolution process

(6) Save the optimal solution, and establish the GA-Fuzzy Control strategy embedded in the EV model of MATLAB/Advisor for simulation

3.2.2. Particle Swarm Optimization. PSO is a type of global random search algorithm based on swarm intelligence. It simulates the migration and swarm behavior in the process of bird swarm foraging. When solving specific problems, in the target search space, by combining the individual optimal solution and the group optimal solution, the optimal solution of the target area is searched iteratively [33–36]. A flowchart of the PSO is shown in Figure 8.

In the D-dimensional target search space, the initial population is composed of n particles, where the position and velocity of the i\(^{th}\) particle are D-dimensional vectors, shown as follows:

\[
X_i = (x_{i1}, x_{i2}, x_{i3}, \ldots, x_{iD}), \quad i = 1, 2, 3, \ldots, n. \tag{12}
\]

\[
V_i = (v_{i1}, v_{i2}, v_{i3}, \ldots, v_{iD}), \quad i = 1, 2, 3, \ldots, i. \tag{13}
\]

The optimal positions searched by the \(i^{th}\) particle and the entire particle swarm are the individual extremum and global extremum, respectively, shown as follows:

\[
P_b = (p_{i1}, p_{i2}, p_{i3}, \ldots, p_{iD}), \quad i = 1, 2, 3, \ldots, n. \tag{14}
\]

\[
G_b = (p_{g1}, p_{g2}, p_{g3}, \ldots, p_{gD}). \tag{15}
\]

After the individual and global extremum are updated, the particle updates its own speed and position according to the current position and speed and the distance from the optimal particle; the update rule is

\[
V_{id} = \omega V_{id} + c_1 \cdot \text{random}(0, 1) (p_{id} - x_{id}) + c_2 \cdot \text{random}(0, 1) (p_{gid} - x_{id}), \tag{16}
\]

\[
x_{id} = x_{id} + V_{id}.
\]

where \(\omega\) is the inertia factor (adjusting the global optimization ability and local optimization performance) and \(c_1\) and \(c_2\) are acceleration constants, where the former is the individual learning factor of each particle and the latter is the social learning factor of each particle. These are usually set as \(c_1 = c_2 \in [0, 4]\).

Based on a PSO algorithm to optimize the control strategy, the steps of building PSO-Fuzzy Control are as follows:

(1) Initialization algorithm: set the maximum number of iterations to 80, number of particles to 65, maximum speed to 0.5, and minimum speed to \(-0.5\)

(2) Initialize particle swarm: randomly generate particles with different positions and velocities in the target search space

(3) Evaluate particles: calculate the fitness of particles according to the evaluation criteria

(4) Update the optimum: update the optimal position experienced by particles and groups

(5) Judgment condition: whether the optimal fitness of particles meets the requirements, or whether the iterations are terminated

(6) The optimal solution is saved, and the PSO-Fuzzy Control strategy is embedded into the EV vehicle model of MATLAB/Advisor for simulation

3.3. Dynamic Programming. In order to compare the control performance of GA-Fuzzy Control and PSO-Fuzzy Control more accurately, this paper proposes a dynamic programming (DP) algorithm to calculate the theoretical minimum energy consumption of HESS. DP algorithm is usually used to solve multistage decision-making optimization problems, which are decomposed into subproblems and solved step by step. Because HESS energy management strategy can be considered as a multistage decision-making problem in
In order to confirm the effect of algorithm optimization, the fuzzy control strategy of a HESS optimized by the GA and PSO algorithms is examined. The improved EV model in MATLAB/Advisor is used for simulations. The following simulation driving cycles are used: UDDS, NEDC, and ChinaCity. A schematic diagram of the operation is shown in Figure 9. The cycle conditions of the three different countries and regions can effectively test the performance of the optimized HESS.

4.1. Analysis of Simulation Results. To evaluate the battery protection performance of the energy management strategy (EMS) optimized by different algorithms, as shown in Figure 10, the battery working currents for different driving cycles are compared. It can be seen that, based on the three conditions, the output current fluctuation of the battery is more stable in the simulation process. From Table 1, in the conditions of UDDS, NEDC, and ChinaCity, the peak current of GA-Fuzzy Control is lower than that of PSO-Fuzzy Control by 35.6001 A, 19.9046 A, and 46.5270 A, respectively.

In general, the economy of the vehicle can be evaluated by examining the fuel economy of the vehicle. As this study is based on an EV, other losses are ignored, and the energy consumption of the HESS is regarded as the economic evaluation standard of the entire vehicle. Figure 11 shows the total energy consumption of two different strategies for simulations in various operating conditions. It can be seen from the figure that, in three driving cycles, the total energy consumption when using GA-Fuzzy Control and PSO-Fuzzy Control as energy management strategies is lower than that before optimization. This verifies the effectiveness of the algorithm optimization.

Compared with the data in Table 1, in the operating conditions of UDDS, NEDC, and ChinaCity, the total energy consumption of GA-Fuzzy Control decreased by 2.4489%, 9.0604%, and 2.5332%, respectively, compared with that before optimization. The energy consumption of PSO-Fuzzy Control decreased by 1.0859%, 0.9659%, and 0.2650%, respectively. The simulation results of the two strategies show that the total energy consumption of the control strategy optimized by the GA is lower. Combined with the comparison results of the working current of the battery, the optimization effect of the GA, in terms of protection of the battery and the battery life stability, is better, which helps save more energy.

Keeping the simulation conditions unchanged, this paper uses the DP algorithm to calculate the theoretical minimum energy consumption of HESS, which is listed in Table 1 for comparison. Compared with the theoretical minimum energy consumption, the simulation results of GA-Fuzzy Control under three drive cycles increased by 0.44%, 0.35%, 0.52%, respectively. This proves that the control strategy proposed in this paper is approximately the best for the optimization of HESS energy consumption.

4.2. Discussion. The GA and PSO algorithms have many features in common. After the population is randomly initialized, both of them use fitness function to evaluate the
Figure 9: Operation diagram of three driving cycles.

Figure 10: Battery current for three driving cycles. (a) UDDS, (b) NEDC, and (c) ChinaCity.
system and search randomly according to the fitness function.

In this paper, based on the control strategy of the hybrid power system of the pure electric vehicle, under the same optimization conditions, the fuzzy rules are optimized by using the GA and PSO. By comparing the control effects of GA-Fuzzy Control and PSO-Fuzzy Control, the accuracy of the two algorithms is evaluated. The results show that the GA is more accurate.

In [38, 39], the two algorithms are also used for research. Reference [38] focuses on the optimization of kinetic parameters of biomass pyrolysis. The results show that the PSO based on the three-component parallel reaction mechanism of biomass pyrolysis has the advantages of being closer to the

<table>
<thead>
<tr>
<th></th>
<th>Peak current (A)</th>
<th>Energy consumption (×10^6 J)</th>
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<tbody>
<tr>
<td>Fuzzy Control</td>
<td>UDDS 6.7501</td>
<td>NEDC 6.2845</td>
</tr>
<tr>
<td></td>
<td>ChinaCity 5.7359</td>
<td></td>
</tr>
<tr>
<td>GA-Fuzzy Control</td>
<td>UDDS 53.4040</td>
<td>NEDC 6.5848</td>
</tr>
<tr>
<td></td>
<td>ChinaCity 5.7151</td>
<td></td>
</tr>
<tr>
<td>PSO-Fuzzy Control</td>
<td>UDDS 62.9496</td>
<td>NEDC 6.2238</td>
</tr>
<tr>
<td></td>
<td>ChinaCity 5.5906</td>
<td></td>
</tr>
<tr>
<td>DP</td>
<td>UDDS 89.0041</td>
<td>NEDC 6.6768</td>
</tr>
<tr>
<td></td>
<td>ChinaCity 5.7207</td>
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</tbody>
</table>

Figure 11: Energy consumption for three driving cycles. (a) UDDS, (b) NEDC, and (c) ChinaCity.
global optimal solution and having faster convergence speed than the GA. In [39], two models of algorithms are established and applied to Iran’s oil demand forecast. The results show that the demand estimation models of the two algorithms are in good agreement with the observed data, but the PSO model has the best performance.

In the case of binary distribution or discrete distribution of the data in this paper, crossover and mutation operations in the GA are very helpful to find the global optimum, and the effect is better than the gradual approximation of PSO. In [40, 41], for global optimization with continuous value, PSO optimization has memory function. It moves to global and local optimal direction in each iteration and can approach the optimal solution faster. It has strong optimization performance and fast optimization speed.

5. Conclusions

Based on the characteristics of poor life stability and limited battery life of an EV as a new energy vehicle, this paper studied an EMS and optimized the management strategy to reduce the energy consumption of the HESS and protect the battery life.

(1) Aimed at the semiactive battery load structure of the HESS of a pure electric vehicle, a fuzzy control strategy was selected as the power EMS, and the control framework was constructed based on an EV model in MATLAB/Advisor. The output power ratio of the battery and ultracapacitor was controlled through the vehicle demand power and SOCs of the battery and ultracapacitor to achieve the purpose of optimal management.

(2) The energy consumption per unit mileage was set as the evaluation standard of the algorithm. GA and PSO were used to improve the fuzzy control strategy in the software, establish the GA-Fuzzy Control and PSO-Fuzzy Control strategies, and conduct a simulation based on the operating conditions of UDDS, NEDC, and ChinaCity. The results showed that both algorithms can optimize the energy management and control strategy of the energy system, and the GA had better optimization performance. The GA showed better protection and economy in the simulation to meet the requirements for the endurance of pure electric vehicles equipped with a HESS.

(3) The DP algorithm is used as the benchmark method to calculate the theoretical minimum energy consumption of HESS in this simulation environment. Compared with the simulation results of GA-Fuzzy Control, it is verified that the control strategy proposed in this paper is approximately optimal for the optimization of HESS energy consumption.

(4) Both GA and PSO can optimize fuzzy control strategies, but the time-consuming algorithm is not suitable for real-time optimization. The optimization method used in this article is only applicable when the simulation drive cycle is known in advance.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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