

Research Article

Online Optimal Energy Distribution of Composite Power Vehicles Based on BP Neural Network Velocity Prediction

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In this paper, an online optimal energy distribution method is proposed for composite power vehicles using BP neural network velocity prediction. Firstly, the predicted vehicle speed in the future period is obtained via the output of a BP neural network, where the current vehicle driving state and elapsed vehicle speed information is used as the input. Then, according to the predicted vehicle speed, an energy management method based on model predictive control is proposed, and online real-time power distribution is carried out through rolling optimization and feedback correction. Cosimulation results under urban drive cycle show that the proposed method can effectively improve the energy efficiency of composite power sources compared with the commonly used method with the assumption of prior known driving conditions.

1. Introduction

Zero-emission pure electric clean vehicles, which can effectively solve the problems of environmental pollution and resource shortage in the automotive field, are the most valuable and significant research direction at present [1–4]. The current problems of pure electric vehicles are as follows. Firstly, the power battery as a single power source cannot meet the endurance requirements and power performance requirements of electric vehicles, especially under acceleration and climbing conditions. Secondly, frequent charging and discharging will affect the life of the power battery, and the high power output current will also cause certain damage to the power battery and affect the working life. In addition, pure electric vehicle with single power source cannot recover regenerative braking energy, which leads to partial energy loss and reduces energy utilization. Therefore, it is necessary to find an auxiliary energy source with high specific power to improve the power performance and energy utilization of pure electric vehicles.

Supercapacitor has the advantages of high power, long cycle life, and fast charging and discharging speed, but it has low energy density and weak energy storage capacity [5]. Therefore, the composite power system composed of power battery and supercapacitor can not only meet the requirements of vehicle power performance but also recover braking energy, increase driving range, and improve energy efficiency. Unlike electric vehicles with a single power source, the composite power source involves the power distribution of two power sources, so it is necessary to design an optimal control strategy for energy management. The current research on energy management strategies of composite power supplies can be roughly divided into two categories: rule-based and optimization-based energy management control strategies. The rule-based energy management control strategy is mainly divided into logic threshold control based on deterministic rules [6] and fuzzy control based on fuzzy rules [7]. Its obvious advantage is that the control rules are simple and easy to implement, but it relies on engineering experience to set rules, which is difficult to adapt to the real-time changes of different driving

conditions, and cannot give full play to the advantages of composite power system. The optimization-based energy management control strategy uses global optimization [8–10] and instantaneous optimization [11–13] to obtain the optimal solution according to the selected objective function and corresponding constraints. Dynamic programming algorithm based on optimal control theory and recursive thought is considered to be a more effective method [14, 15]. However, the optimal control decision can only be obtained offline when the information of vehicle state and driving condition is fully known, which cannot be solved online. Model predictive control [16] searches for the optimal control sequence in the finite time domain at each sampling instant, which makes it possible to achieve the online optimal solution. However, this method largely relies on effective prediction of future vehicle speed.

There are mainly two kinds of speed prediction methods. One is to use some kind of prediction algorithm, such as exponential prediction [17] and random prediction [18], which requires an accurate mathematical model; the other is to predict the future vehicle speed with the help of vehicle navigation system [19] or identifying the repeated working conditions of special working vehicles [20], which needs the help of GPS system or prior driving condition information and is not suitable for off-road vehicles without positioning system and perception radar. The back propagation (BP) neural network algorithm is a multilayer feedforward network trained according to error back propagation algorithm and is one of the most widely applied neural network models [21]. BP neural network can learn and store the mapping relationship of various input-output models, which is very suitable for vehicle speed prediction. This paper presents an intelligent model prediction energy management method based on BP neural network velocity prediction. Firstly, the BP neural network model is used to predict the future vehicle speed accurately. Then, based on the principle of model predictive control, the optimal control quantity at each moment is obtained through rolling optimization and feedback regulation, so as to achieve the instantaneous optimal distribution of composite power system. Finally, simulation results from the whole composite power vehicles model obtained by integrating the composite power Simulink model into the ADVISOR verify the improved performance compared with the commonly used method.

The remainder of this paper is organized as follows. In Section 2, the composite power vehicle model is given. The proposed online optimal power distribution strategy of composite power vehicles is introduced in Section 3. Simulation model and the simulation results of the proposed approach based on the whole vehicle model from advisor are also analyzed in Section 4. Finally, the conclusions are drawn in Section 5.

2. Modeling of Composite Power Vehicles

Considering the weight, initial cost, energy efficiency, and control strategy implementation, the composite power topological structure, as shown in Figure 1, is selected in this paper. The lithium battery pack as the main energy source of

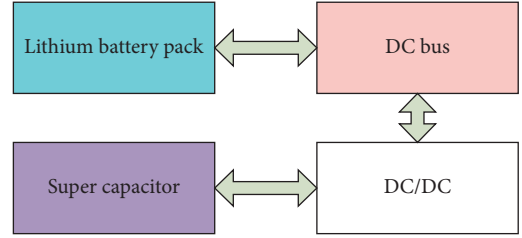


FIGURE 1: Composite power topological structure.

composite power supply system is directly connected with the DC bus. Meanwhile, the supercapacitor bank is connected in series with DC/DC and then connected to the DC bus in parallel with the power battery pack. The above structure not only enables the power battery to respond to the energy demand of the load in time but also makes the transient performance of the supercapacitor connected in series with the DC/DC converter easier to control, thereby greatly improving the energy conversion efficiency of the composite power supply system.

After the topological structure of the composite power supply system is determined, it is necessary to match the design of the series or parallel number of power battery packs and the capacity of the supercapacitor group according to the vehicle system parameters, as shown in Table 1.

The rated voltage of the motor selected in this paper is 384 V; according to the characteristics of vehicle lithium battery, the series number of lithium battery can be calculated as

$$N_b = \frac{U_M}{U_b}, \quad (1)$$

where N_b is the series number of lithium batteries, U_M is the rated voltage of the motor, and U_b is the voltage of single lithium battery. If the rated voltage of lithium battery is selected as 2.2 V, then we have $N_b = 172$. Considering that the internal resistance increases when the battery declines, the number of units in series is taken as 180.

The capacity of lithium batteries can determine the number of lithium batteries in parallel. For the determination of battery capacity, the driving range requirements of the vehicle are mainly considered. The calculation formula is as follows:

$$s = \frac{W \cdot v}{P_m \cdot \eta}, \quad (2)$$

where s is the driving range of the electric vehicle, W is the energy stored in the battery, v is the driving speed of the vehicle, P_m is the power required for constant speed driving of the vehicle, and η is the efficiency of the transmission system.

The calculation formula of battery energy is written as

$$W = Q_e \cdot U_e \cdot N_b \cdot \eta_{\text{dod}}, \quad (3)$$

where Q_e is the rated capacity of battery cell, U_e is the rated voltage of single battery, N_b is the number of battery cells,

TABLE 1: The parameters of composite power vehicle.

Vehicle parameters			
Full load mass	18000 kg	Rolling radius	478 mm
Curb weight	12000 kg	Centroid height	1307 mm
Distance (centroid to front axle)	3846 mm	Rolling resistance coefficient	0.012
Drive ratio	6.2	Air drag coefficient	0.55
Wheelbase	5950 mm	Windward area	8.7 m ²
Corresponding power demand for vehicle performance index			
	Maximum speed	Maximum gradient	Acceleration performance
Dynamic performance index	70 km/h	18% and 12 km/h	0–50 km/h–20 s
Motor power demand	74 kW	122 kW	128 kW
Permanent magnet synchronous motor performance parameters			
Maximum power	150 kW	Maximum torque	3300 nm
Maximum speed	2600 r/min	Rated voltage	384 V
Rated current	200 A	Pole pair number	2

and η_{dod} is the discharge depth, which is determined according to the characteristics of the selected battery; here, we have $\eta_{\text{dod}} = 80\%$.

The rated capacity of lithium battery selected in this paper is 10 Ah, and other parameters have been determined in the previous introduction, so the number of parallel connections required is 6. That is to say, the matching result of power batteries in this paper is 180 single batteries in series and 6 batteries in parallel.

The parameter matching of supercapacitor should be considered from two aspects: braking energy recovery and peak power of vehicle during driving. The parameter configuration of supercapacitor should meet the following formula:

$$E_u = \frac{1}{2} N_u C_u (U_{u_{\text{max}}}^2 - U_{u_{\text{min}}}^2), \quad (4)$$

$$E_u \geq (P_{\text{max}} - P_a) \cdot T,$$

where N_u is the series number of supercapacitors, C_u is the capacity of supercapacitor unit, $U_{u_{\text{max}}}$ is the maximum voltage of supercapacitor unit, $U_{u_{\text{min}}}$ is the minimum voltage of supercapacitor unit, P_{max} is the peak power of vehicle driving process, P_a is the average power of vehicle driving process, and T is the duration of peak output power.

In this paper, the rated voltage of supercapacitor is 2.7 V, and the rated capacity of monomer is 9500 F. The series connection of supercapacitor is 180, and the number of parallel connections of supercapacitor is 2, which can meet the maximum energy demand.

After the parameter calculation of each part, the whole vehicle model can be established in the ADVISOR software, as shown in Figure 2. In this model, the power required by the cycle is transferred to the power bus module through the vehicle module, wheel module, main reducer module, transmission module, and motor controller module. The power required by the bus is provided by the composite power supply through the energy management strategy.

After setting all vehicle parameters and vehicle simulation cycle conditions, the secondary development based on ADVISOR software is completed. Click the “run” button to enter the simulation output interface to view and analyze the simulation results. The simulation output interface of

ADVISOR mainly includes simulation result output window of each component, output window of vehicle energy utilization result, acceleration and climbing test result output window, energy utilization window, and output result drawing window. For the composite power electric vehicle, it is necessary to check the output of simulation results of each component, which is generally the curve of vehicle speed following the driving condition, the change curve of battery SOC and current, and the change curve of torque out of composite power, as shown in Figure 3.

3. Online Optimal Energy Distribution Strategy of Composite Power Vehicles

The main purpose of the energy management strategy of the composite power bus is to reasonably distribute the output power of the two power sources online, which can not only meet the power performance requirements of the vehicle but also ensure that the lithium battery works in the appropriate working area and avoid overcharge and over discharge. In this paper, the real-time optimization of power allocation is based on model predictive control method. Consider the following control system model:

$$\begin{cases} \dot{x} = f(x, u, v), \\ y = g(x, u, v), \end{cases} \quad (5)$$

where x is the SOC of the supercapacitor, the output power of lithium is selected as the control input u , v is the velocity, the system output $y = [\text{SOC}_b \text{ SOC}_u]^T$, SOC_b is the state charge of battery, and SOC_u is the state charge of capacitor.

At each sampling time k , the optimal objective function in the prediction time domain is

$$J = \int_k^{k+P} (w_b (\text{SOC}_b(t) - \text{SOC}_0)^2 + w_u (\text{SOC}_u(t) - \text{SOC}_1)^2) dt, \quad (6)$$

where w_b and w_u are the weight coefficients of the corresponding item, respectively, SOC_0 is the SOC reference value of power, SOC_1 is the SOC reference value of supercapacitor, and P is the prediction time domain.

The constrained inequality equation of the optimization problem is as follows:

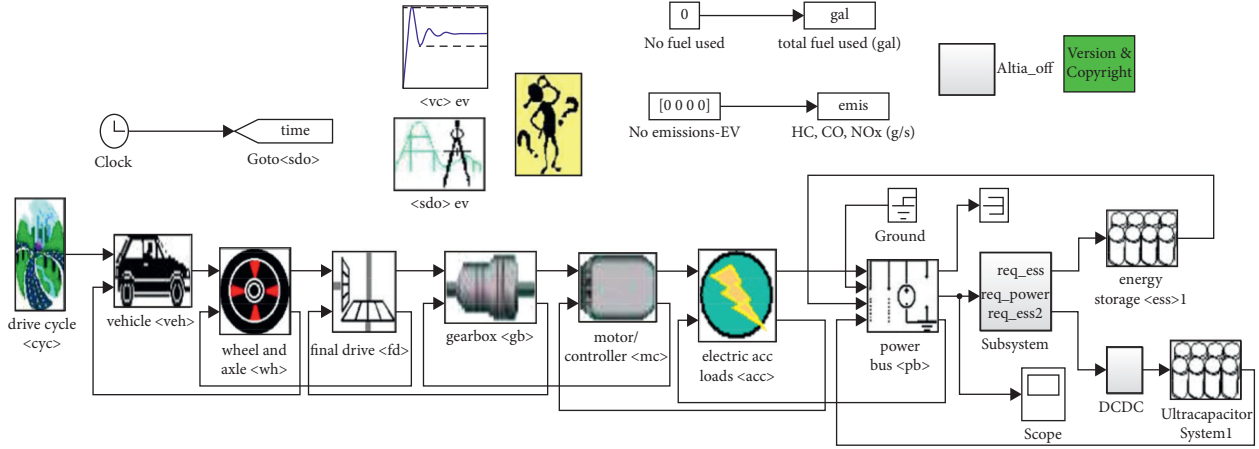


FIGURE 2: The electric vehicle model combined with the proposed composite power in ADVISOR.

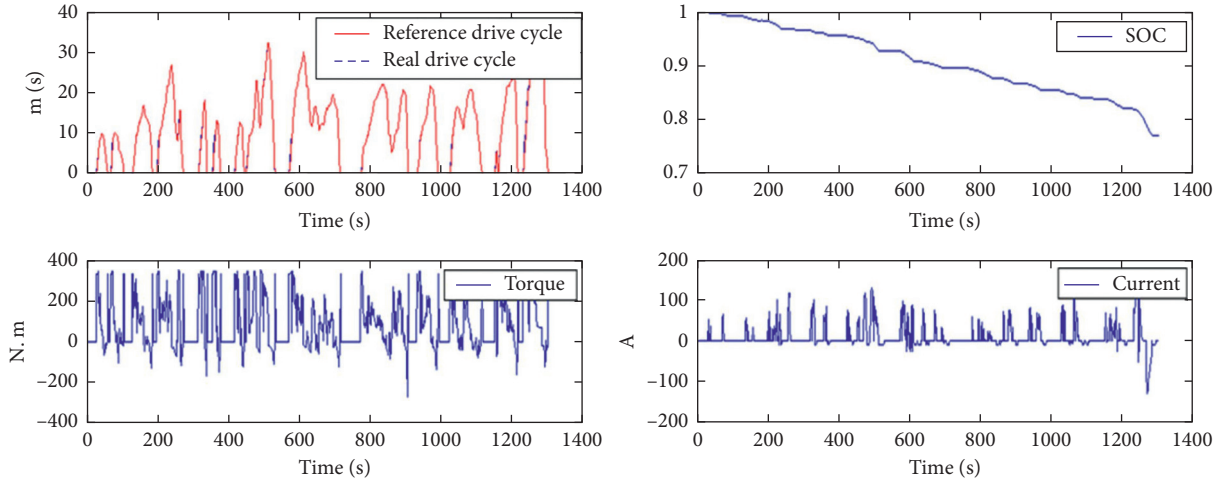


FIGURE 3: Simulation results from ADVISOR.

$$\begin{cases}
 I_{b \min} \leq I_b(t) \leq I_{b \max}, \\
 I_{u \min} \leq I_u(t) \leq I_{u \max}, \\
 SOC_{b \min} \leq SOC_b(t) \leq SOC_{b \max}, \\
 SOC_{u \min} \leq SOC_u(t) \leq SOC_{u \max}, \\
 P_{b \min} \leq P_b(t) \leq P_{b \max}, \\
 P_{u \min} \leq P_u(t) \leq P_{u \max},
 \end{cases} \quad (7)$$

where $I_{b \min}$ and $I_{b \max}$ are the minimum and maximum of the battery charging and discharging current, respectively, $I_{u \min}$ and $I_{u \max}$ are the minimum and maximum of the capacitor charging and discharging current, respectively, $SOC_{b \min}$ and $SOC_{u \min}$ are the minimum of the SOC of battery and capacitor, respectively, $P_{b \min}$ and $P_{b \max}$ are the minimum and maximum power of the battery, respectively, and $P_{u \min}$ and $P_{u \max}$ are the minimum and maximum power of the capacitor, respectively.

The system model is discretized when solving the optimization problem, because of the prediction time domain is short, and the feasible area of SOC is small at every time. Dynamic programming algorithm can be used to solve

optimization problems online and in real time. Assuming that $U^*(k) = [u^*(k), \dots, u^*(k+P-1)]$ is the sequence of optimal control variables in the prediction time domain, the control variable adopted by the system at the current time is

$$u(x(k)) = u^*(k). \quad (8)$$

The core idea of predictive control is to solve an optimization problem in the finite prediction time domain at each sampling time and calculate the optimal control sequence in the prediction time domain, but only implement the optimal control at the sampling time and discard other control variables, and then repeat the process at the next sampling time. In order to overcome the problem existing in energy management strategy which needs to know the whole cycle in advance, we proposed an energy management method based on BP neural network speed prediction which can predict the future speed of the working condition through the neural network model. The model predictive algorithm is solved by rolling optimization to obtain the optimal control quantity, improve the energy utilization efficiency of the composite power system, and realize the optimization of energy management.

The energy management method of composite power supply based on neural network speed prediction, as shown in Figure 4, comprises the following steps.

Step 1: according to the historical speed information and the current driving state of the vehicle, a neural network speed prediction model, as shown in Figure 5, is established to obtain the predicted speed of time K in the future;

Generally speaking, the three-layer BP neural network has met the learning requirements of most nonlinear systems. The three-layer structure of BP neural network is shown in Figure 5. The first layer is the input layer, which mainly undertakes the task of receiving data input; the second layer is the hidden layer, which is composed of neurons and activation functions to describe the input-output mapping relationship; the third layer is the output layer, which is used to generate specific information of output data. The activation function of BP neural network is hyperbolic tangent S-type function, which is defined as follows:

$$n = W + y_0 + b, \quad (9)$$

$$y = \tan \operatorname{sig}(n) = \frac{1 - e^{-2n}}{1 + e^{-2n}},$$

where n is the cumulative output, y_0 is the input layer neuron output, y is the hidden layer neuron output, W is the weight value, and b is the bias value. The main disadvantage of BP neural network is that the convergence speed of sample training is slow, and local minimum may appear.

Before the speed prediction of BP neural network, network training should be carried out first, and the optimal weight and threshold value can be obtained through network training. In this paper, the above-mentioned urban congestion driving conditions (NYCC) and urban unimpeded driving conditions (UDDS), as shown in Figure 6, are selected as training samples. At each sampling time of the cycle, the characteristic parameters of the driving cycle in the past 10 s are calculated. Through the experimental analysis, five characteristic parameters which can distinguish the two driving cycles are selected as part of the prediction model input, such that average speed is \bar{v} (m/s), maximum speed v_{\max} (m/s), maximum acceleration a_{\max} (m/s²), standard deviation of vehicle speed f_v (km/h), and idle time ratio P_i .

The speed in the past period is taken as a part of the BP neural network model input, such that

$$N_{\text{in}} = \bar{v}, v_{\max}, a_{\max}, f_v, P_i, v_k, v_{k-1}, \dots, v_{k-H_h}, \quad (10)$$

where \bar{v} represents the average speed, v_{\max} represents the maximum speed, a_{\max} represents the maximum acceleration, f_v represents the standard deviation of vehicle speed, P_i represents the proportion of idle time, H_h is the length of historical vehicle number vector,

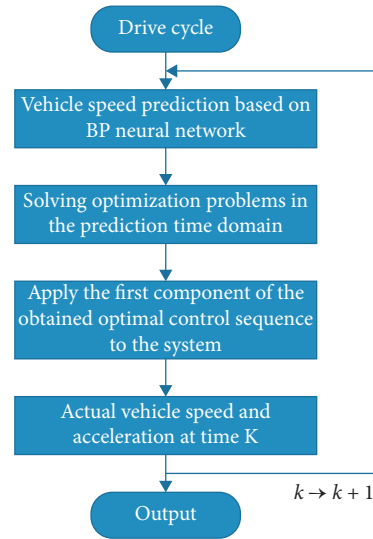


FIGURE 4: Energy management strategy flow chart.

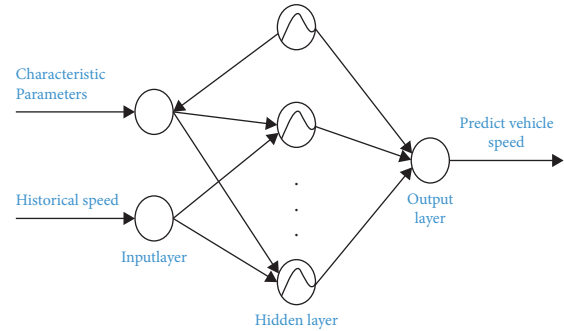


FIGURE 5: Topology of BP neural network.

and $v_k, v_{k-1}, \dots, v_{k-H_h}$ is the vehicle speed at each time, respectively.

The output of BP neural network model which represents the predicted speed in a period of time in the future is expressed as

$$N_{\text{out}} = v_{k+1}, v_{k+2}, \dots, v_{k+p}. \quad (11)$$

After the overall structure and input/output are determined, the BP neural network can be trained. The typical urban road conditions are selected for speed prediction. The number of hidden layer neurons is selected as 50, and the training algorithm is trainscg with fixed variable ratio. Figure 7 shows the speed prediction results and speed error of BP neural network. Figure 8 shows the change of mean square error during training. Figure 9 shows the fitting result of BP neural network corresponding data measured by regression line. As can be seen from the training results, the speed prediction method proposed in this paper can accurately predict the speed.

Step 2: according to the predicted speed obtained in step 1, the required power of the motor is calculated;

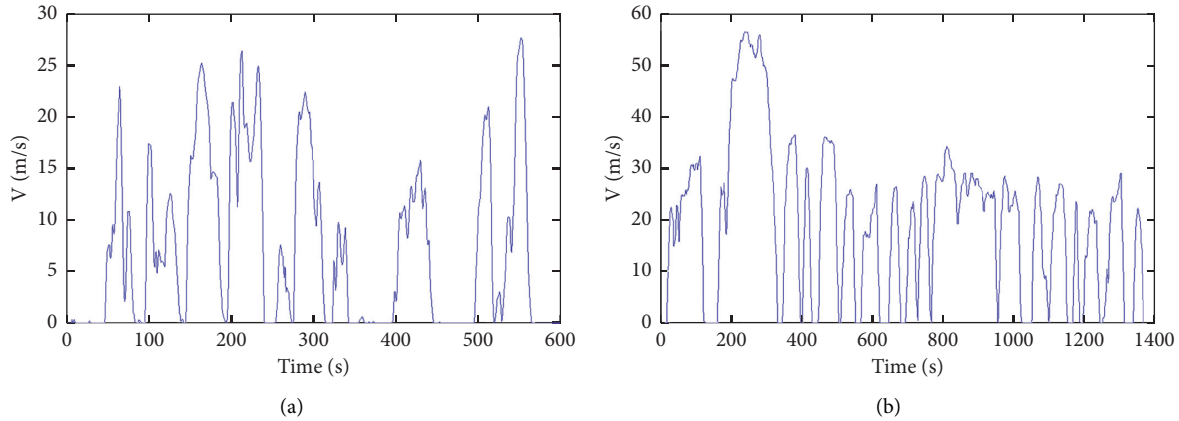


FIGURE 6: Sample of driving cycle conditions. (a) NYCC cycle conditions. (b) UDSS cycle conditions.

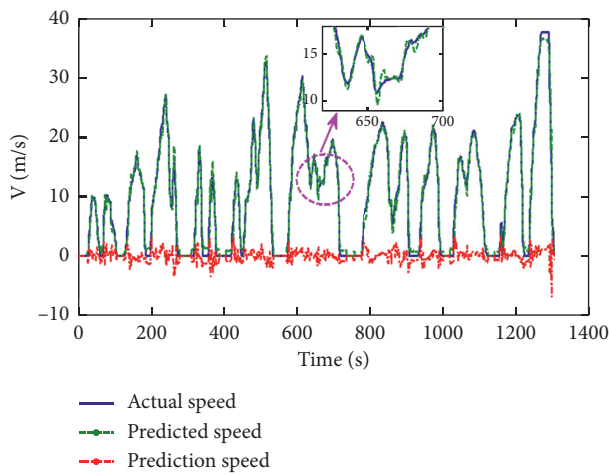


FIGURE 7: Result of vehicle speed prediction.

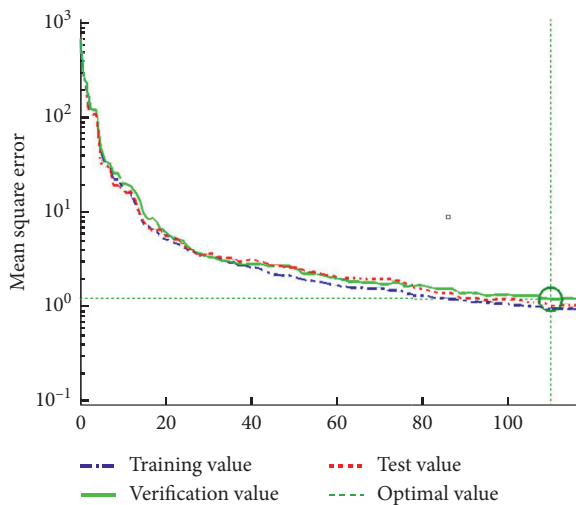


FIGURE 8: Mean square error during training.

Step 3: according to the power demand in step 2, the model predictive control algorithm is used to solve the optimal control sequence in time domain from K time;

Step 4: the first control variable of the optimal control sequence obtained in step 3 is applied to the vehicle system to correct the predicted value at the next moment;

Step 5: repeat the operation process of step 4 at the time of $K + 1$ until the optimal control quantity of the whole system is obtained.

4. Cosimulation between ADVISOR and MATLAB/Simulink

In order to verify the effectiveness of the optimal power distribution method proposed for composite power vehicles using BP neural network velocity prediction, the ADVISOR vehicle simulator was used to conduct simulation analysis combined with the MATLAB/Simulink environment. The sampling interval was set as 1 s, and the time domain was predicted to be 5 s. The initial condition of battery SOC and supercapacitor SOC was in full state. Simulation results of the proposed control strategy under typical road conditions are shown in Figures 10–12.

It can be seen from Figures 10–12 that both lithium battery and supercapacitor have energy consumption and braking energy recovery. Meanwhile, the battery SOC curve drops smoothly, and the energy consumption is relatively small. Supercapacitor has more braking energy recovery, which can prevent the battery from large current output and ensure the service life of the battery. At the same time, the proposed optimal power distribution method can improve the energy utilization efficiency of the composite power supply system.

In order to further illustrate the effectiveness of the optimal power distribution strategy proposed in this article, we also give the compared simulation results of other three commonly used control strategies such as rule-based logic threshold [5], fuzzy control [6], and dynamic programming (DP) [13]. The comparison results are shown in Figures 13 and 14.

It can be seen from Figures 13 and 14 that the SOC consumption curve of the battery under the proposed method based on BP speed prediction is relatively flat, and

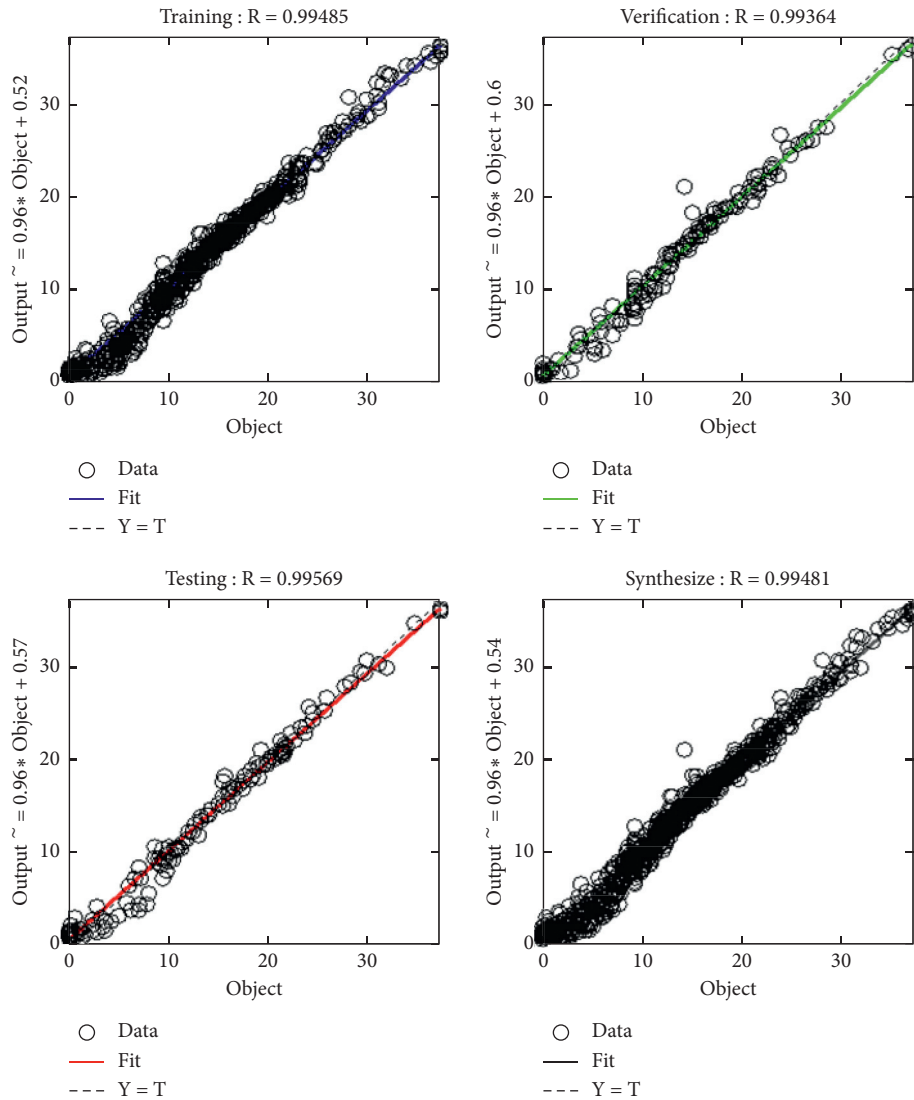


FIGURE 9: The results of data regression analysis.

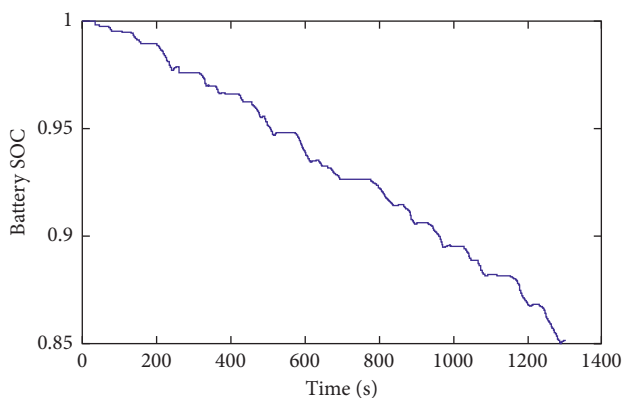


FIGURE 10: Battery SOC change curve.

the energy consumption is similar to the result of the dynamic programming algorithm and is lower than the rule-based logic threshold control and fuzzy control. The SOC curve of supercapacitor fluctuates greatly, which can provide

large current output and more braking energy recovery. At the same time, notice that the SOC consumption curve of the supercapacitor under each control strategy does not vary greatly. This is because the total energy of the composite power supply is calculated and matched according to the total cruising range of the passenger car, and the simulation working condition is only 1304 s in a typical city driving cycle. This will cause the power battery and supercapacitor to remain in a high SOC state, but the control effect can still be analyzed according to the specific numerical conditions.

In order to further compare the control effects of different control strategies, the total energy consumption is compared. It can be seen from Table 2 that the total energy consumption of the dynamic programming algorithm using global optimization is the smallest, the total energy consumption of using the rule-based energy management strategy is the largest, and the fuzzy control algorithm is the second. However, the dynamic programming algorithm can only obtain the optimal distribution rate of the composite power system through offline calculation when the entire

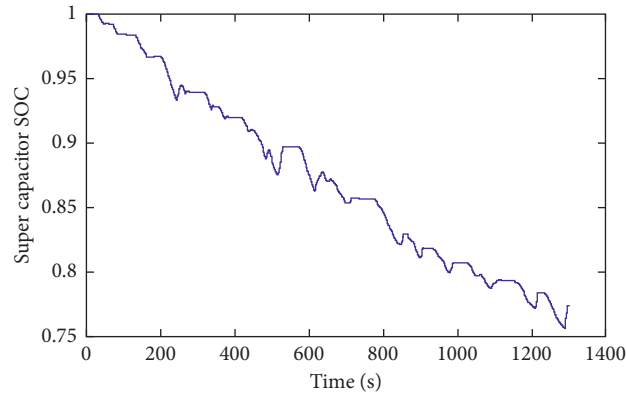


FIGURE 11: Supercapacitor SOC change curve.

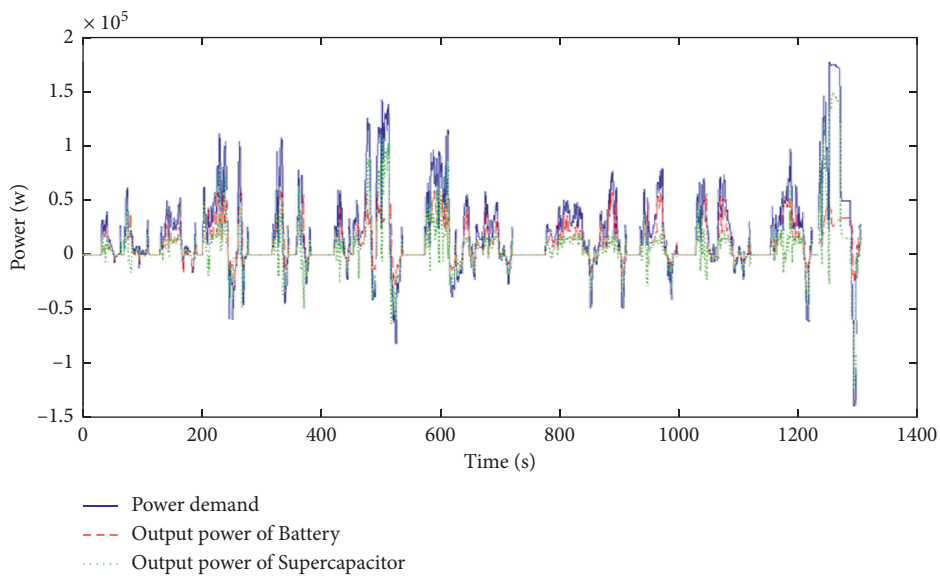


FIGURE 12: Power splitting of composite power supply.

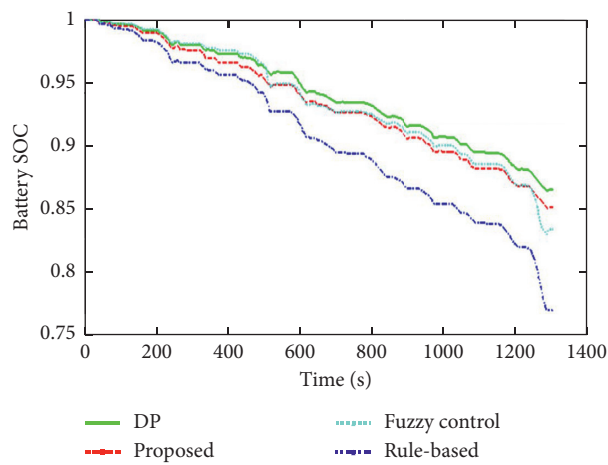


FIGURE 13: Comparative analysis of SOC change of battery under different control strategies.

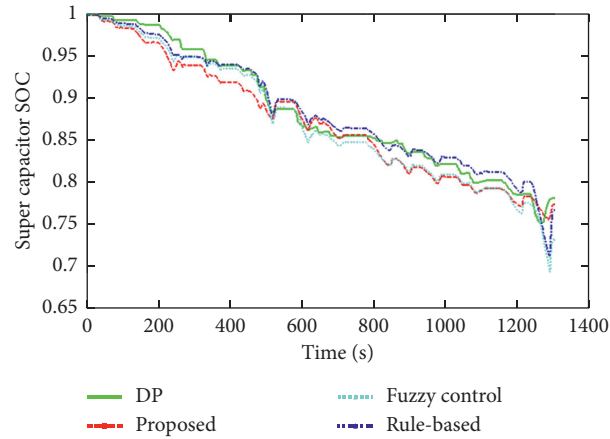


FIGURE 14: Comparative analysis of SOC change of supercapacitors under different control strategies.

TABLE 2: Total energy consumption.

Control strategy	Battery SOC at termination time	Capacitor SOC at termination time	Total energy consumption
Dynamic programming	0.8649	0.7818	0.3533
Proposed	0.8508	0.7737	0.3755
Fuzzy control	0.8331	0.7320	0.4349
Rule-based	0.7686	0.7670	0.4640

driving cycle conditions are known and cannot be implemented online and in real time. The total energy consumption of the proposed online optimal power distribution method based on BP speed prediction can not only reach a level close to that of the dynamic programming algorithm but also can be implemented online for practical application.

5. Conclusions

This paper proposes an online optimal energy distribution method of the composite power supply composed of lithium battery and supercapacitor for electric buses. The compared simulation results show that the proposed method can achieve the optimal energy distribution between lithium battery and supercapacitor based on the online prediction of future driving speed and do not require the assumption of prior known driving conditions in the general dynamic programming method, which is more convenient for practical application.

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 that there are no conflicts of interest regarding the publication of this article.

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