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Driving Ranges Prediction of Pure Electric Vehicle with Dual – Energy Storage System Based on BP Neural Network

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Abstract

Compared with the traditional fuel vehicle, the pure electric vehicle has excellent characteristics in the emissions and energy use. But its driving ranges are much shorter than the traditional fuel vehicle. It has become a bottleneck problem for the development of electric vehicle. It is difficult to establish the accurate model of driving ranges in the actual working condition. Its main reason is that the influence factors of electric vehicle driving ranges and driving ranges have a non-linear relationship. BP neural network can map the complex non-linear relationship and has strong non-linear fitting ability. Compared the driving ranges of fuzzy control with fuzzy PI control in pure electric vehicle with dual-energy storage system, the results of simulation experiment indicate that the fuzzy PI control can extend the driving rages of electric vehicle. The maximum value of the average error is 2.66% in BP neural network prediction.

Keywords: *pure electric vehicle with dual-energy storage system, driving ranges, BP neural network, prediction.*

1. The Influence Factors of Driving Ranges

Driving ranges are the mileages that the battery is from fully charged to the specified experiment end. It is one of the economic performance of electric vehicles [1-2]. The influence factors of driving ranges are composed of rolling resistance coefficient, frontal area, vehicle quality, mechanical transmission efficiency and so on. These factors are the same as the traditional fuel vehicles. In addition, its factors are also composed of battery performance, auxiliary system, energy loss of low voltage electrical system and the efficiency of motor control system. The battery performance consists of discharge current, discharge voltage, environmental temperature and the depth of discharge. The depth of discharge is a very important factor which is reflected by battery SOC (state of charge). The paper focuses on the influence of the battery SOC and ultra-capacitor SOC in driving ranges of electric vehicles [3].

2. Driving Ranges Calculation

At present, the calculation method of electric vehicles driving ranges is based on the principle which the output power of battery is equal to the energy consumption of electric vehicles operation [4]. The driving force for electric vehicles operation is [5]:

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$$F_t = A \cdot \frac{dV}{dt} + BV^2 + CV + D \quad (1)$$

Where,

$$A=0.4536 \cdot W \quad (2)$$

$$B=0.01 \cdot CD \cdot RHO \cdot AR \quad (3)$$

$$C=0.0199 \cdot W \cdot CRO \cdot \cos(GA) \quad (4)$$

$$D=4.445 \cdot W \cdot CRO \cdot \cos(GA)+4.445W \cdot \sin(GA) \quad (5)$$

Where, W — The weight of the vehicle;
CD — The air resistance coefficient;
RHO — The air density;
AR — The frontal area;
CRO — The rolling resistance coefficient;
GA — The slope angle;
V — The vehicle velocity.

According to the principle which the output power of battery is equal to the energy consumption of electric vehicles operation, the energy of battery can be expressed as:

$$E_B = \frac{F_t S}{\eta \eta_M \eta_C \eta_B \times 3600} \quad (6)$$

Where, F_t — The electric vehicle driving force;
S — The electric vehicle driving ranges;
η — The mechanical transmission efficiency;
η_M — The motor driving efficiency;
η_C — The motor control efficiency;
η_B — The battery discharge efficiency.

Table 1. The Parameters of Pure Electric Vehicle with Dual-energy Storage System

Parameters	Values	Parameters	Values
weight of the vehicle /kg	520	mechanical transmission efficiency	0.92
frontal area /m^2	1.05	motor driving efficiency	0.93
air resistance coefficient	0.35	motor control efficiency	0.96
rolling resistance coefficient	0.015	battery discharge efficiency	0.85

3. Driving Ranges Prediction Based on BP Neural Network

The influence factors of electric vehicle driving ranges and driving ranges have a non-linear relationship, so it is difficult to establish the accurate model of driving ranges in the actual working condition. The neural network has strong non-linear characteristics. And it has also a very good effect on the complex and irregular system.

3.1. The Neural Network Model

Artificial neural network is an intelligent algorithm which processes the data distributed concurrently according to the feature of brain neurons. By adjusting the relationship between nodes and nodes in the network, neural network processes the information. It has strong robustness, fault tolerance, fast operation speed, self-learning and self-adaptive. Moreover, it has strong approximation ability to non-linear complex system [6]. In 1943, psychologist McCelland and mathematician

W.Pitts propose MP model at first according to the basic characteristics of neurons. The model is shown in Figure 1 [7].

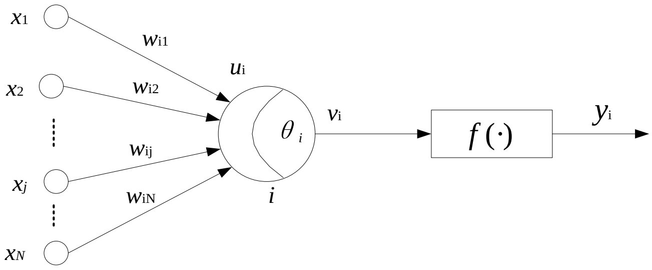


Figure 1. Neural Network Model

Where, x_j (j=1, 2, ... , N) — The input of neuron J;

w_{ij} — Weight(the connection strength of neuron i and j);

u_i — The linear combination of the input;

θ_i — The neuron threshold;

v_i — The value is adjusted by the threshold;

$f(\cdot)$ — The activation function of neuron;

y_i (i=1, 2, ..., N) — The output of neuron i.

$$u_i = \sum_{j=1}^{N} w_{ij} x_j \tag{7}$$

$$v_i = u_i + \theta_i \tag{8}$$

$$y_i = f(v_i) \tag{9}$$

3.2. The Principle and Steps of BP Neural Network Algorithm

BP neural network has been widely used in pattern recognition, artificial intelligence, system prediction and other fields. In 1980s, Dabid Runelhart, Geoffrey Hinton, Ronald Williams, David Parker and Yann Le Cun put together a BP neural network model [8].

3.2.1. The Main Idea of BP Neural Network: The learning process of BP neural network consists of forward transmission and reverse transmission of the signal. When the signal is transferred forward, the input layer of the network is imported input signal. After the input signal is processed by each hidden layer, it is transferred to the output layer. If the actual output of the output layer does not meet the desired values, then the system will enter the reverse transmission of the error. The reverse transmission of the error is that the output error is transferred to input layer through some form layer by layer. During the process of the reverse transmission error, the error is allocated the full unit of each layer. And then the error of each layer unit is obtained. The deviation of each unit is modified according the error amount. BP algorithm is that the weights are adjusted during forward transmission of the signal and reverse transmission of the error constantly, namely, the process of BP network learning and training. The process will carry out recurrently until the network output error is reduced to the set value or the number of learning in advance is attained [9-10].

3.2.2. The Structure of BP Neural Network: BP neural network is composed of input layer, hidden layer and output layer. The structure of BP neural network which has two hidden layers is introduced in the paper as it is enough to show any output form of the input function. The structure of BP neural network is shown in Figure 2 [11].

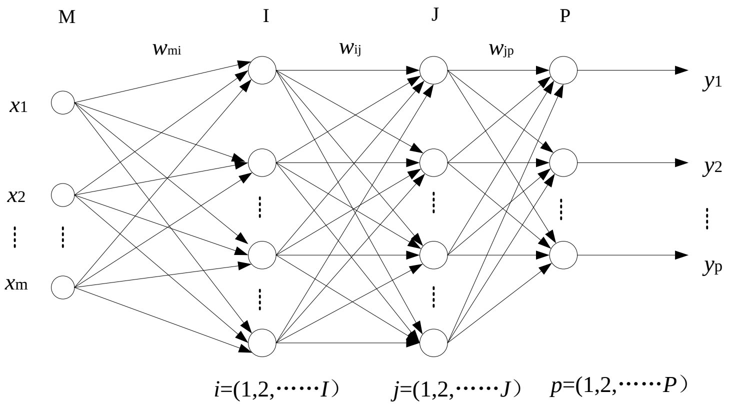


Figure 2. The Structure of BP Neural Network with Two Hidden Layers

If M input signals are contained in the input layer of neural network and x_m is represented by one of the input signals. The first hidden layer contains I neurons and i is represented by one of the neurons. The second hidden layer contains J neurons and j is represented by one of the neurons. The output layer contains P neurons and p is represented by one of the neurons. The weight between the input layer and the first hidden layer is represented by w_{mi}. The weight between the first hidden layer and the second hidden layer is represented by w_{jp}. The input signal of the neuron is represented by u and the output signal is represented by v. The superscripts of u and v are represented layers and the subscripts are represented some neurons in the layer. For example, u_i^1 is represented that the input signal is the ith neurons in the first hidden layer [12].

3.2.3. The Learning Algorithm of BP Neural Network: According to the structure of BP neural network in Figure 2, the learning algorithm of BP neural network is derived. The training sample set is X=[X_1, X_2, …, X_k, …, X_N], where any training sample is X_k=[x_{k1}, x_{k2}, …, x_{kM}]′ and $k \in$ (1, 2, …, M). The output of actual measurement is Y_k=[y_{k1}, y_{k2}, …, y_{kP}]′ and the output expected value is D_k=[d_{k1}, d_{k2}, …, d_{kP}]′. Let n represent the number of the iterations, then the forward transmission of the input signal can gets [13]:

$$u_i^I = \sum_{m=1}^{M} w_{mi} x_{km} \qquad v_i^I = f(u_i^I) = f(\sum_{m=1}^{M} w_{mi} x_{km}) \quad i=1, 2, \ldots, I \tag{10}$$

$$u_j^J = \sum_{i=1}^{I} w_{ij} v_i^I \qquad v_j^J = \varphi(u_j^J) = \varphi(\sum_{i=1}^{I} w_{ij} v_i^I) \quad j=1, 2, \ldots, J \tag{11}$$

$$u_p^P = \sum_{j=1}^{J} w_{jP} v_j^J \qquad v_p^P = \Psi(u_p^P) = \Psi(\sum_{j=1}^{J} w_{jp} v_j^J) \quad p=1, 2, \ldots, P \tag{12}$$

$$y_{kp} = v_p^P = \Psi(\sum_{j=1}^{J} w_{jp} v_j^J) \tag{13}$$

The error signal of the p neurons can be expressed as:

$$e_{kp}(n) = d_{kp}(n) - y_{kp}(n) \tag{14}$$

The learning network error can be calculated through the output of the neural network. Then forward transmission of neural network is finished. In the reverse transmission process of the neural network, the transmission direction of error signals is from the back to the front. They transfer layer by layer and modify the weights. The structure of error backward transmission is shown in Figure 3 [14].

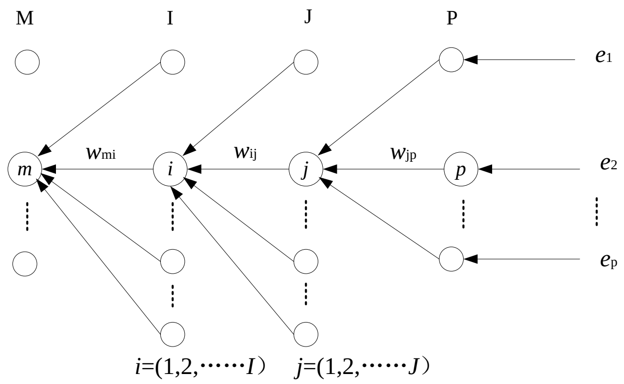


Figure 3. The Structure of BP Neural Network Error Backward Transmission

The modified weights between output layer P and hidden layer J are obtained through the derivation of the error backward transmission. They can be expressed as:

$$w_{jp}(n+1)= w_{jp}(n) + \Delta w_{jp}(n) \tag{15}$$

The modified weights between the first hidden layer I and the second hidden layer J are derived similarly. They can be expressed as:

$$\Delta w_{ij}(n) = \eta \delta_j^J(n) v_j^J(n) \tag{16}$$

Where, $$\delta_j^J(n) = \sum_{p=1}^{P} \delta_p^P(n) \times w_{jp}(n) \times \varphi'(u_j^J(n)) \tag{17}$$

The modified weights between any point of the first hidden layer and any point of the input layer M can be expressed as:

$$\Delta w_{mi}(n) = \eta \delta_i^I(n) x_{km}(n) \tag{18}$$

Where, $$\delta_i^I(n) = f'(u_i^I(n)) \sum_{j=1}^{J} \delta_j^J(n) w_{ij}(n) \tag{19}$$

$\delta_i^I(n)$ in equation (18) can be obtained through the equation (17).

$$f'(u_i^I(n)) = \frac{\partial v_i^I(n)}{\partial u_i^I(n)} = v_i^I(n)(1-v_i^I(n)) \tag{20}$$

BP neural network completes forward transmission of the signal and backward adjustment of error. The whole process is a learning or an iterative process of BP network. BP neural network algorithm will pass through a lot of iterations until the learning error reaches the required precision. Performance indicators to measure BP neural network are composed of learning time, iterative times and error precision.

3.2.4. The Steps and Flow Chart of BP Neural Network Algorithm: The algorithm steps of BP neural network can be summarized:

(1) Weight initialization: Let $w_{mi}(0)$, $w_{ij}(0)$ and $w_{jp}(0)$ represent a group of very small non-zero values.

(2) Define the input, output and desired output of BP neural network and determine t h e i r

structural parameters. The network input is $X_k=[x_{k1}, x_{k2}, \ldots, x_{kM}]$, where $k \in (1, 2, \ldots, N)$ and N represents the number of training samples. The output of actual measurement is $Y_k(n)=[y_{k1}(n), y_{k2}(n), \ldots, y_{kP}(n)]$, where n represents the number of iterations. The output expected value is $D_k=[d_{k1}, d_{k2}, \ldots, d_{kP}]$.

(3) Input training samples: Input training samples respectively $X=[X_1, X_2, \ldots, X_k, \ldots, X_N]$.

Let the learning samples in this time be X_k, where $k \in (1, 2, \ldots, N)$.

(4) Forward signal transmission: Calculate the output of network according to the equation

(13) and the training error of sample X_k according to the equation (14).

(5) Reverse signal transmission: Update the weight according to the equation (15) and judge if K is bigger than N. If K is bigger than N, then the step (6) will be carried out. Otherwise the step (3) will be carried out.

(6) Calculate the total training error of the network. If the value can reach the required precision, then the training will be stop. Otherwise the step (3) will be carried out and begin the next training.

The flow chart of BP neural network algorithm is shown in Figure 4.

3.3. Driving Ranges Prediction Based on BP Neural Network

3.3.1. Extract the Sample Data: The driving ranges of the fuzzy control and fuzzy PI control for pure electric vehicle with dual – energy storage system are predicted in five typical operating conditions. The ultra-capacitor SOC decreases faster than the battery. The simulation will stop when the ultra-capacitor SOC decreases the safety limit value. Considering the redundancy of the ultra-capacitor SOC, the safety limit value of the ultra-capacitor SOC is set to 0.4. The training data of the neural network are shown in Figure 5 to Figure 9.

In figures, when the ultra-capacitor SOC decreases to 0.4, the electric vehicle driving time and its driving ranges of fuzzy PI control are greater than fuzzy control in five typical operating conditions. The curves of driving ranges fluctuate greatly as the vehicles start, stop and change the speed continuously in the driving process. The values of the battery SOC, the ultra-capacitor SOC and driving ranges are extracted in Matlab/Simulink in Figure 5 to Figure 9. The mutational data are removed according to denoising experience. After the data are processed, a part is used as training data and the other part is used as test data.

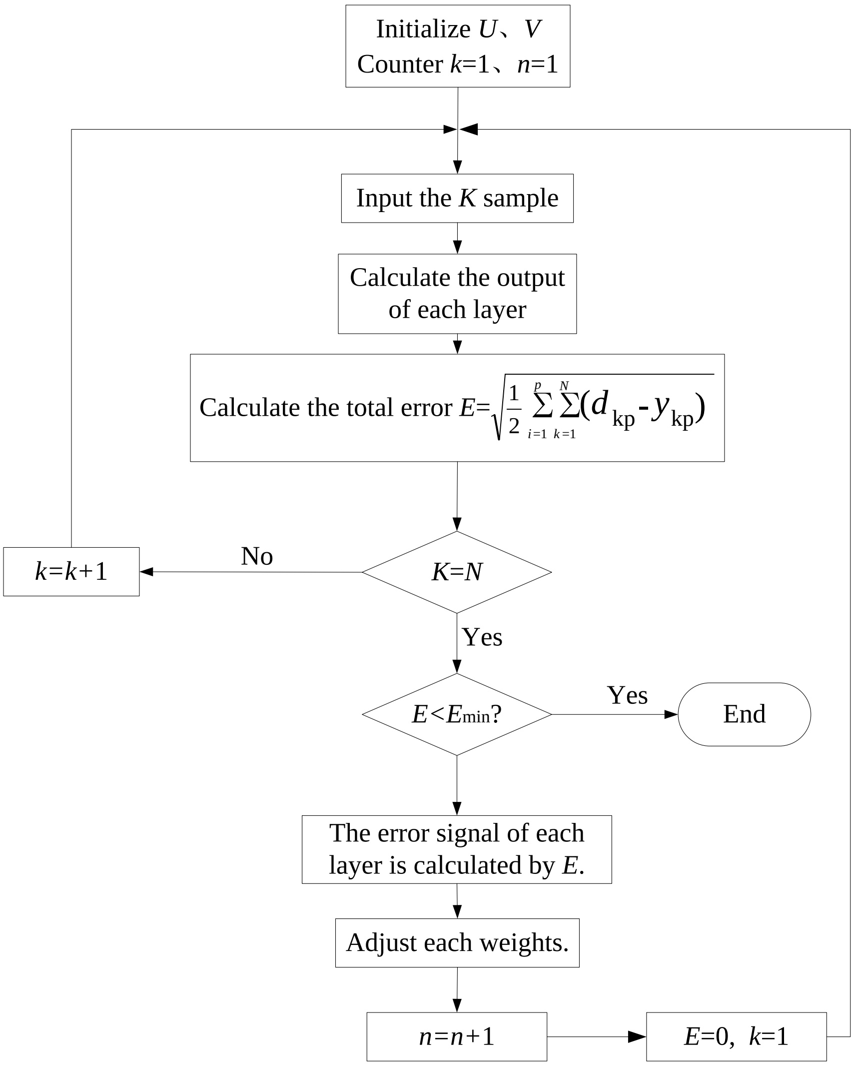


Figure 4. Flow Chart of BP Neural Network Algorithm

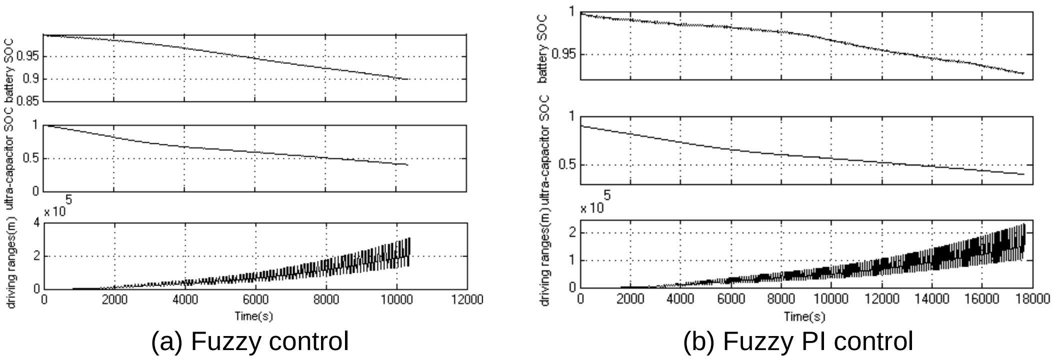
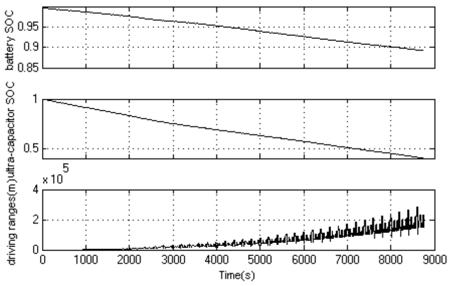
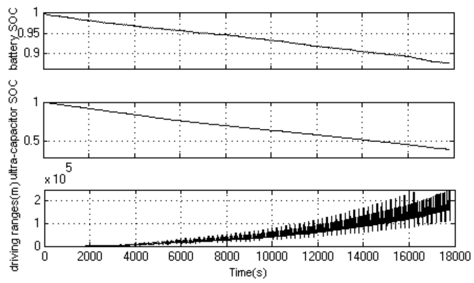


Figure 5. The Neural Network Training Sample Data of City Six Cycles

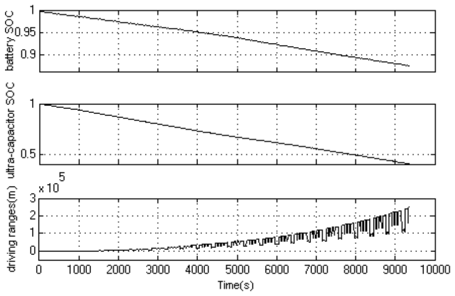


(a) Fuzzy control

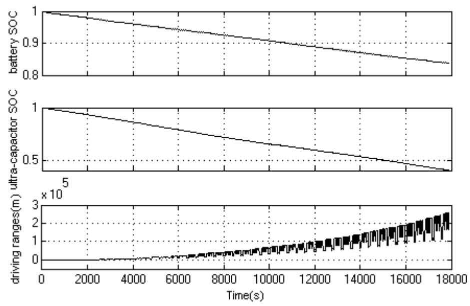


(b) Fuzzy PI control

Figure 6. The Neural Network Training Sample Data of ECE Driving Cycle

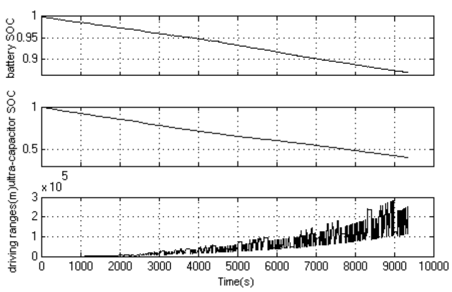


(a) Fuzzy Control

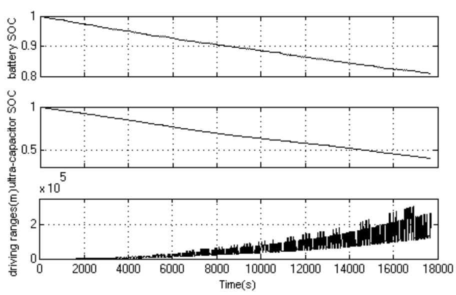


(b) Fuzzy PI Control

Figure 7. The Neural Network Training Sample Data of EUDC Driving Cycle

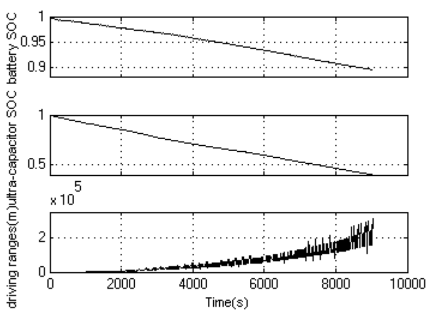


(a) Fuzzy Control

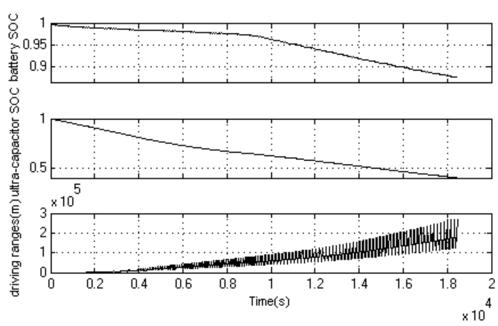


(b) Fuzzy PI Control

Figure 8. The Neural Network Training Sample Data of Japan1015 Driving Cycle



(a) Fuzzy Control



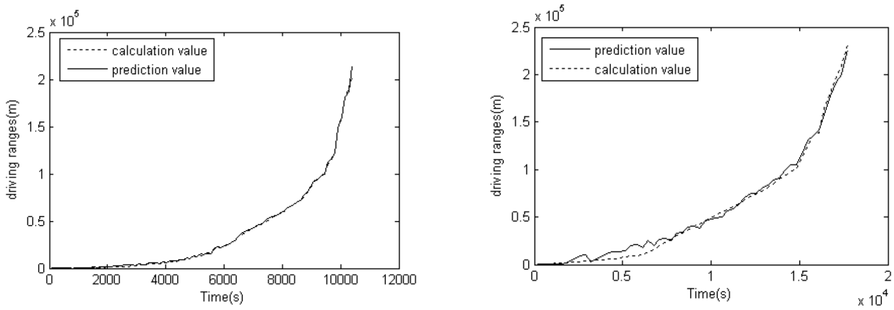
(b) Fuzzy PI Control

Figure 9. The Neural Network Training Sample Data of NEDC Driving Cycle

3.3.2. Data Normalization: The sample data are normalized before they are trained. They are zoomed according to a certain scaling, which ranges from 0 to 1 or from -1 to 1. It can improve the convergence speed of the network and reduce the difficulty of weight adjustment. The specific normalization method is that the maximum value of the samples X_{N} is $X_{\max}$ and its minimum value is $X_{\min}$. X_N^* is represented by the sample of normalization and it should meet:

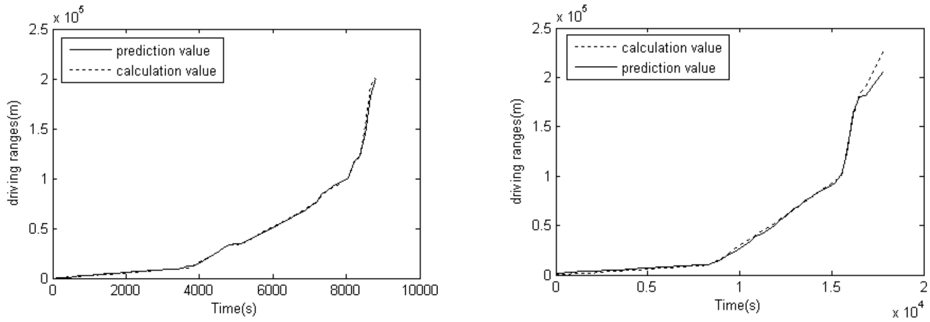
$$X_N^* = \frac{X_{\mathrm{N}} - X_{\min}}{X_{\max} - X_{\min}} \tag{21}$$

3.3.3. The Results and Analysis of the Simulation: The simulation experiments are done in order to analyse the performance of BP neural network algorithm in the driving ranges of the electric vehicle. The number of hidden layer in BP neural network is 2. The input layer is the battery SOC and ultra-capacitor SOC. The output layer is the calculated value of driving ranges in theory. The output layer function is purelin ( ). The hidden layer function is tansig ( ). The training function is trainlm. The iteration number is 50. The minimum error of training goal is 0.01. The learning rate is 0.05. The maximum training steps are 1000. The simulation will end when the system reaches the error value or the maximum training steps. The prediction results are shown in Figure 10 to Figure 14.



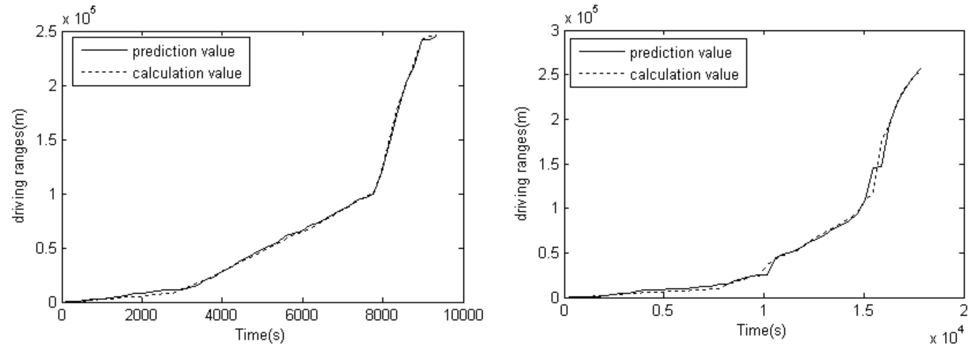
(a) Fuzzy Control (b) Fuzzy PI Control

Figure 10. The Prediction Results of City Six Cycles



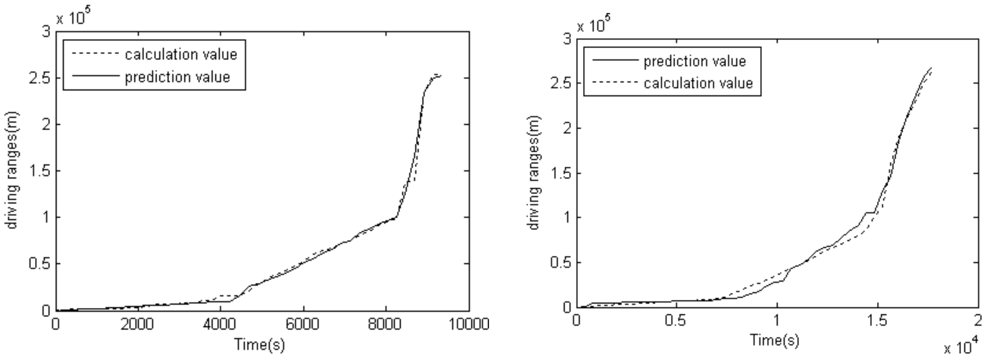
(a) Fuzzy Control (b) Fuzzy PI Control

Figure 11. The Prediction Results of ECE Driving Cycle



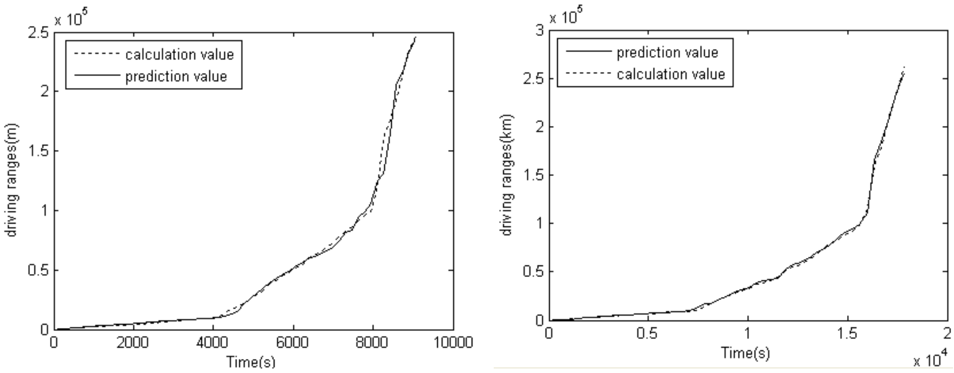
(a) Fuzzy control (b) Fuzzy PI control

Figure 12. The Prediction Results of EUDC Driving Cycle



(a) Fuzzy Control (b) Fuzzy PI Control

Figure 13. The Prediction Results of Japan1015 Driving Cycle



(a) Fuzzy Control (b) Fuzzy PI Control

Figure 14. The Prediction Results of NEDC Driving Cycle

In figures, the prediction values and theoretical values of driving ranges are very close in five typical operating conditions. Moreover, the driving ranges of fuzzy PI control system are farther than that of fuzzy control. It shows that fuzzy PI control algorithm can fully embody the advantages of energy storage system. It can make full use of the characteristics of ultra-capacitor with high charge and discharge current and reduce the high current effect on the battery in the start, stop and acceleration of the electric vehicle. It can also prolong the life of the battery and increase the driving ranges of electric vehicles. Compare the driving ranges of two kinds of control strategies in five typical operating conditions, the results are shown in Table 2.

Table 2. The Comparison of Two Kinds of Control Strategies in Five Typical Operating Conditions

Operation conditions	Fuzzy control			Fuzzy PI control		
	Calculation value(km)	Prediction value(km)	Average error(%)	Calculation value(km)	Prediction value(km)	Average error(%)
city six cycles	201.14	214.43	1.27	230.64	225.14	2.66
ECE	201.08	200.06	1.2	226.33	206.51	2.2
EUDC	245.8	245.04	1.21	255.57	258.29	1.11
Japan1015	253.42	252.59	1.19	262.79	268.1	1.12
NEDC	246.21	249.02	1.05	262.52	258.84	1.16

In fuzzy control algorithm, the maximum value of driving ranges prediction is 252.59km in Japan 1015 and the minimum value of driving ranges prediction is 200.06km in ECE driving cycle. In fuzzy PI control algorithm, the maximum value of driving ranges prediction is 268.1km in Japan 1015 and the minimum value of driving ranges prediction is 206.51km in ECE driving cycle. It shows that fuzzy PI control algorithm can prolong the driving ranges of electric vehicles. In addition, although the prediction values and theoretical values of two kinds of control algorithms are very close, there are still errors in BP neural network algorithm. The average error of fuzzy PI control algorithm is maximal in city six cycles and the maximum value is 2.66%.

Compare the prediction of two kinds control algorithms in five typical operating conditions, the results are shown in Table 3.

Table 3. The Comparison of Driving Ranges in Five Typical Operating Conditions

Operation conditions	Fuzzy control	Fuzzy PI control	Increase (%)
city six cycles	214.43	225.14	5
ECE	200.06	206.51	3.2
EUDC	245.04	258.29	5.4
Japan1015	252.59	268.1	6.1
NEDC	249.02	258.84	3.9

The driving ranges of fuzzy PI control algorithm are farther than fuzzy control algorithm in Table 3. It respectively increases 5%, 3.2%, 5.4%, 6.1% and 3.9% in five typical operating conditions. The incremental rate of driving ranges in Japan 1015 driving cycle is maximal and the incremental rate of driving ranges in ECE driving cycle is minimal. Therefore, the optimizational effect of energy between the battery and the ultra-capacitor in fuzzy PI control algorithm is better than in fuzzy control algorithm. It can improve the economic performance of electric vehicles.

4. Conclusions

BP neural network is adopted as the prediction algorithm of driving ranges in the paper. The model of BP neural network is established by the sample data. Then, select the appropriate parameters for the network. At last, train the sample and enable it to reach the training error requirement. The prediction data are imported into trained neural network model during driving ranges prediction. The simulation results show that the driving ranges of fuzzy PI control algorithm is farther than fuzzy control algorithm. The maximum margin of increase is up to 6.1%. The maximum average error of BP neural network algorithm is 2.66%.

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