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DRIVING CYCLE CONDITION IDENTIFICATION MODEL BASED ON LONG SHORT-TERM MEMORY ALGORITHM

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Abstract. *This paper proposes an online recognition model of driving cycle conditions. The model, designed for new energy vehicles, aims to realize the adaptability of the energy management strategy under uncertain driving cycle conditions. Firstly, the original driving cycle database is constructed based on the standard conditions in which characteristic parameters are extracted, and the parameter dimension reduction is carried out according to the correlation between each characteristic parameter. Secondly, the original driving database is divided into four categories by a hierarchical clustering algorithm, and a representative driving condition is selected from each category to form the typical driving cycle datasets. Then, an online recognition model of driving conditions based on long short-term memory (LSTM) algorithm is constructed for the "typical driving cycle datasets", the optimal recognition period and update period are determined, and the recognition effect is verified. Finally, the accuracy of driving condition recognition based on a long short-term algorithm can reach 98.7805%, so it shows that the driving cycle condition recognition algorithm based on LSTM can better identify driving cycle conditions online.*

Keywords: Deep learning, Recognition model, Driving cycle condition, Recognition period, Cluster analysis, Long short-term memory neural network

1. **Introduction.** Nowadays, the mainstream new energy vehicle control strategy depends on a certain driving cycle condition. The construction of an online identification model conforming to the real driving cycle is of great engineering significance for the construction of the vehicle control strategy [1,2].

At present, more and more scholars have studied the recognition strategy of the driving cycle state. Xu et al. [3] used the t-distributed stochastic neighbor embedding (t-SNE) algorithm to reduce the dimensionality of the selected 22 feature parameters. 12 state-of-the-art supervised learning (SL) regression models were compared, and the extra tree (ET) algorithm had the highest recognition accuracy of 90.26%. Tao and Zhang [4] studied the problem of a multilayer perceptron neural network (MLPNN) as a classifier for the condition recognition algorithm. A genetic algorithm (GA) is used to optimize the

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structure, parameters, sampling, and update window size of the neural network, and hybrid encoding/decoding and structure operators are designed to optimize the neural network classifier. The different characteristic parameters of driving cycles are extracted, and the representative driving cycles are screened based on the Euclidean algorithm in [5,6]. The k-means clustering algorithm based on genetic optimization was proposed to identify typical driving cycle conditions [7,8]. Regarding building a driving condition recognition model, five characteristic parameters of real-time driving cycle conditions were extracted and a driving condition recognition model based on a fuzzy algorithm to realize the calibration of real-time driving conditions and standard driving conditions was introduced in [9,10]. [11] built the driving condition recognition models based on probabilistic neural networks (PNN), learning vector quantization (LVQ), and back propagation (BP) neural network algorithms, respectively, and the recognition effects were comparatively analyzed. A condition recognition strategy based on a learning vector quantization neural network (LVQ) to identify a random condition online was designed in [12-14]. A deep learning framework for human action recognition was proposed to accurately predict the location of the objects in [15]. This algorithm extracts the appearance-based and structural information, and each frame of the action sequences is evaluated for spatial features. Yu et al. [16] proposed an analytical platform for continuously processing large volumes of sensor data and detecting irregular patterns in any sensor by predicting its possible future values.

For domestic and foreign researchers in the selection of feature parameters, dimensionality reduction methods, classification algorithms, and recognition models to carry out research on driving condition recognition, among which SL, GA, PNN, LVQ, and BP can achieve a certain degree of accuracy recognition algorithms, but the stability and accuracy of the model need to be improved. Deep learning algorithms have the advantages of strong learning ability, more neural network layers, and high algorithm stability. They are widely used in face recognition, traffic light modeling, unmanned vehicle control, etc. [17,18], but not many applications in driving cycle condition recognition.

The structure of this paper is as follows: 1) Build the original driving cycle database, select the characteristic parameters of the driving cycle according to the correlation, and then carry out hierarchical cluster analysis on the original driving cycle database based on the characteristic parameters; 2) The online driving cycle recognition model is established by using the long short-term memory (LSTM) algorithm in deep learning to determine the best combination of recognition period and update period; 3) The identification algorithm model is established to verify its identification effect. Based on the above methods, new ideas are provided for the design of a new energy vehicle control strategy.

2. **Construction of the Typical Driving Cycle Datasets.** The vehicle driving cycle, also known as the driving cycle, is a time-varying speed sequence, which can be used as the basis for calculating the vehicle's energy consumption economy or emission level, and is also the basic premise for formulating the cycle identification strategy [19]. Therefore, reasonable typical driving cycle datasets should be constructed before developing a cycle recognition strategy, and the datasets should contain comprehensive road characteristics.

2.1. **The original driving cycle database.** The 30 standard driving conditions, which consider the characteristics of urban, suburban, and high-speed driving conditions, are selected in this section and combined into the original driving cycle database as the original data for constructing the typical driving cycle datasets, as shown in Table 1.

2.2. **Selection of the characteristic parameters of the typical driving cycle datasets.** A driving cycle curve can describe the driving process of a vehicle and can

TABLE 1. Standard driving cycle condition

Number	Symbol	Number	Symbol	Number	Symbol
1	1015_6PRIUS	11	INDIA_HWY	21	REP05
2	ARB02	12	INDIA_URBAN	22	SC03
3	BUSRTE	13	LA92	23	UDDS
4	CLCVELAND	14	MANHATTAN	24	UDDSHDV
5	CSHVR	15	NEDC	25	UNIF01
6	ECE	16	NYCC	26	US06
7	FTP	17	NYCCOMP	27	US06_HWY
8	HL07	18	NYCTRUCK	28	WVUCITY
9	HWFET	19	NewYorkBus	29	WVUINTER
10	IM240	20	Nuremberg36	30	WVUSUB

also reflect information on driving conditions by using characteristic parameters. In this paper, we selected 15 characteristic parameters based on the "Huawei Cup" The 17th China Post-Graduate Mathematical Contest in Modeling, including average speed, maximum speed, average acceleration, etc., which are selected to describe the information of the original driving cycle database, as shown in Table 2. The correlation among 15 characteristic parameters could be analyzed by Equation (1). The calculation results are shown in Table 3. Dimensionality reduction is performed on the characteristic parameters according to the calculation results.

$$R = \frac{\sum_{i=1}^{n}\left(x_i - \overline{x_i}\right)\left(y_i - \overline{y_i}\right)}{\sum_{i=1}^{n}\left(x_i - \overline{x_i}\right)^2 \sum_{i=1}^{n}\left(y_i - \overline{y_i}\right)^2} \tag{1}$$

where x_i and y_i indicate the feature quantities of the feature parameter, respectively, $\overline{x_i}$ and $\overline{y_i}$ denote average values of the feature quantities, and n is the capacity of characteristic quantity.

TABLE 2. Selection of the feature parameters

Number	Characteristic value	Unit
1	Driving distance	m
2	Acceleration time ratio	%
3	Speed reduction time ratio	%
4	Idling time ratio	%
5	Equal speed time ratio	%
6	Average driving speed	km/h
7	Average speed	km/h
8	Maximum speed	km/h
9	Speed standard deviation	km/h
10	Maximal acceleration	m/s^2
11	Maximum deceleration	m/s^2
12	Average acceleration in the acceleration phase	m/s^2
13	Average deceleration in the deceleration stage	m/s^2
14	Acceleration standard deviation	m/s^2
15	Average acceleration	m/s^2

The larger the correlation coefficient, the more significant the correlation between the two parameters and the greater the overlap of information it represents. Usually, characteristic parameters with a correlation coefficient greater than 0.8 can be replaced by each

TABLE 3. Correlation coefficient between the various characteristic parameters

R	1	2	3	4	5	...	14	15
1	1.000	0.261	0.281	−0.582	0.427	...	0.203	−0.062
2	0.261	1.000	0.671	−0.543	−0.208	...	0.662	0.213
3	0.281	0.671	1.000	−0.475	−0.216	...	0.481	0.396
4	−0.582	−0.543	−0.475	1.000	−0.676	...	−0.257	−0.098
5	0.427	−0.208	−0.216	−0.676	1.000	...	−0.272	−0.162
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
14	0.203	0.662	0.481	−0.257	−0.272	...	1.000	0.409
15	−0.062	0.213	0.396	−0.098	−0.162	...	0.409	1.000

other. To sum up, characteristic parameters numbered 1, 2, 3, 5, 7, 9, 10, 12, 14, and 15 were selected in this paper to express the information on driving cycle conditions.

2.3. **Construction of the typical driving cycle datasets based on hierarchical cluster analysis.** In order to make typical driving cycle datasets representative, the method of hierarchical clustering analysis was used to cluster the original driving cycle database in this contribution. The basic steps are as follows.

1) All initial driving cycle conditions are regarded as one type.

2) The Euclidean distance between various driving conditions is calculated according to the selected sample data. Based on the principle of Euclidean distance minimization, we classify the two classes with the smallest distance into one class and form a new class.

3) Repeat these steps until the new class is unique.

However, before using hierarchical clustering for classification, due to the different unit magnitudes of each feature parameter, the sample data needs to be standardized, according to Equations (2)-(4).

$$y_{i,j} = \frac{(x_{i,j} - \overline{x_j})}{\sqrt{S_j}} \tag{2}$$

$$\overline{x_j} = \frac{1}{n} \sum_{i=1}^{n} x_{i,j} \tag{3}$$

$$S_j = \frac{1}{n} \sum_{i=1}^{n} (x_{i,j} - \overline{x_j})^2 \tag{4}$$

where $\overline{x_j}$ and S_j denote the jth average value and variance of the sample data matrix, and n denotes the number of rows of the sample data matrix.

In addition, according to Equation (5), the normalized sample data was normalized with the aim of compressing the data within the $[0, 1]$ interval,

$$Y_{ij} = \frac{y_{ij} - \min y_{ij}}{\max y_{ij} - \min y_{ij}} \tag{5}$$

where $i = 1, 2, 3, \ldots, 30$; $y = 1, 2, 3, \ldots, 10$.

2.4. **Cluster analysis of the original driving cycle databases.** The sample data matrix of hierarchical clustering (30×10) is composed of 30 original driving cycle databases selected in Section 2.1 and 10 characteristic parameters that can describe the characteristic information of each driving condition after dimension reduction. First, standardize the sample data matrix, complete the hierarchical clustering algorithm code based on the MATLAB platform, cluster the sample data matrix, and finally get the cluster tree of the sample data, as shown in Figure 1.

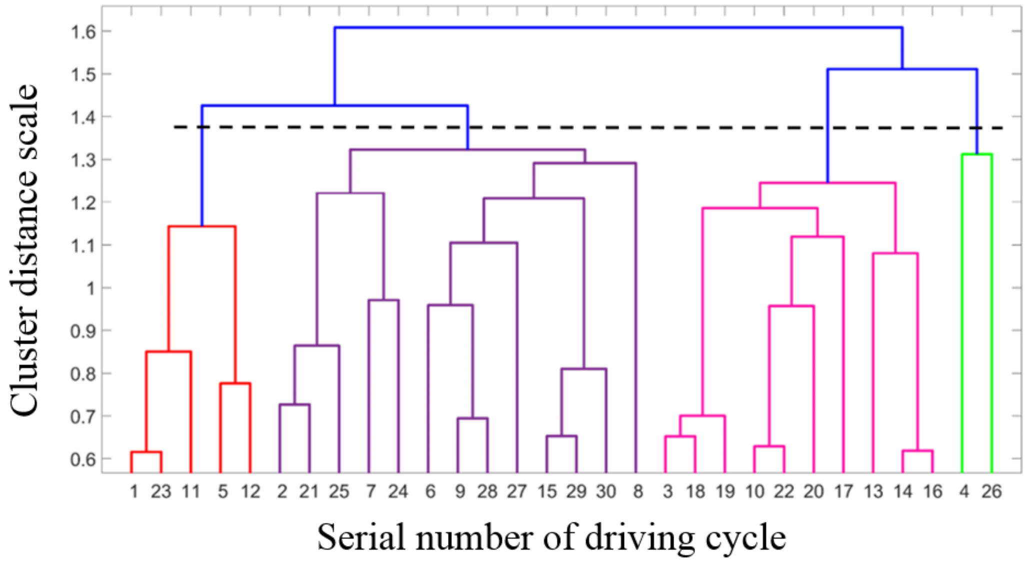


FIGURE 1. Hierarchical clustering analysis results

The sample data is divided into four categories. By analyzing the clustering distance scale, this section divides the original driving cycle databases into four categories, and the classification results are shown in Table 4.

TABLE 4. Hierarchical clustering analysis results

Typical driving cycle category	Number
1	1,23,11,5,12
2	2,21,25,7,24,6,9,28,27,15,29,30,8
3	3,18,19,10,22,20,17,13,14,16
4	4,26

Based on the driving time, driving distance, and average speed, a standard driving condition is selected from each category to represent this type of driving condition. They are Type I standard driving condition: cyc_Manhattan; Class II standard driving condition: cyc_Us06; Class III standard driving condition: cyc_UDDS; Class IV standard driving condition: cyc_Wvuenter, so as to build the typical driving cycle datasets.

3. **Construction of Driving Cycle Recognition Model Based on Deep Learning.** The main idea of cycle identification is to divide the actual cycle into several segments according to a certain time series based on the typical driving cycle datasets. Through the driving cycle identification strategy, the unknown driving cycle segment can be defined as a certain type of driving cycle in the typical driving cycle datasets in [20,21]. In this section, feature parameters used for driving cycle recognition are first selected, then a driving cycle recognition model is designed based on the theoretical basis of long short-term memory (LSTM) in deep learning, and it is trained and verified.

3.1. **Selection of driving condition identification parameters.** In Section 2.2, 15 feature parameters were selected based on the results of the modeling competition. Considering the short recognition period in this section, the feature parameters 6, 12 and 13 in Table 2 were of little significance In order to reduce the amount of calculation, the above three quantities were deleted in this section and the left 12 valid feature parameters were selected for identification, including driving distance, average speed, maximum

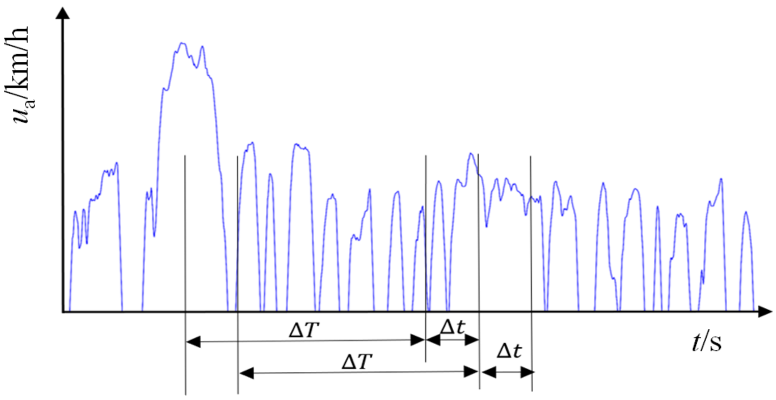


FIGURE 2. Driving cycle fragment division method

speed, maximum acceleration, maximum deceleration, average acceleration, the standard deviation of acceleration, the standard deviation of speed, acceleration time ratio, deceleration time ratio, uniform time ratio, and idle time ratio. Then, the method, as shown in Figure 2 is used to divide driving condition segments and calculate the characteristic parameters of each driving condition segment.

In Figure 2, ΔT denotes the recognition period, and Δt denotes the update period. In this paper, ΔT is 30 s, Δt is 3 s, then divide the driving condition fragments and the characteristic parameters are also solved. Finally, the sample size of each type of driving condition is shown in Table 5.

TABLE 5. Sample capacity of various driving cycle conditions

Driving cycle condition number	Sample capacity
1	351
2	191
3	441
4	531

3.2. **Construction of driving identification model based on LSTM algorithm.** LSTM is a kind of time recurrent neural network that belongs to one of the deep learning algorithms and can solve the long-term dependence problem of RNN (recurrent neural network). LSTM is suitable for processing and predicting important events with very long intervals and delays in time series, usually better than time recurrent neural networks and hidden Markov models (HMM), such as those used in unsegmented continuous handwriting recognition, and autonomous speech recognition, as a nonlinear model, LSTMs can be used as complex nonlinear units to construct larger deep neural networks. Based on the typical driving cycle dataset and the theory of long short-term memory (LSTM) obtained by the hierarchical clustering algorithm, this section constructs an online driving cycle recognition model based on LSTM and verifies its recognition effect.

3.2.1. *Correlation theory of the LSTM.* Long short-term memory (LSTM) neural network in [22], proposed by Hochreiter and Schmidhuber, is a specially structured recurrent neural network (RNN), mainly used to solve the problem of frequent gradient explosion or disappearance of RNN, and has wide applications in the fields of text generation, machine translation, and speech recognition. LSTM is generally composed of multiple single cycles (also known as cells). The basic structure of a single LSTM is shown in Figure 3.

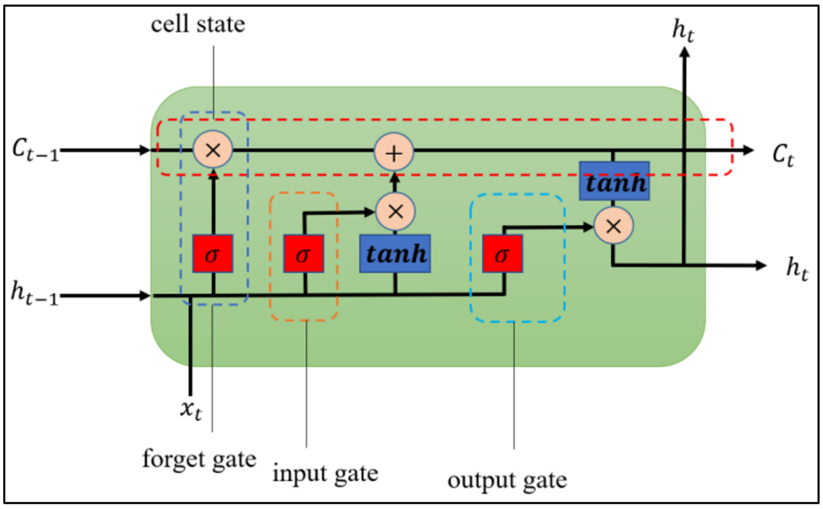


FIGURE 3. Basic structure of LSTM

The basic structure of LTSM mainly includes an *input gate*, *forget gate*, *output gate* and *cell state*, as shown in Figure 3. Three of these gates are mainly used to control the state information. The square in Figure 3 represents the sigmoid activation function. The rectangle in Figure 3 represents the tanh activation function. h_{t-1} denotes the output of the previous moment. x_t denotes the input data of the current moment. h_t denotes the output of the current moment. C_t indicates the state of the cell at the current moment. C_{t-1} indicates the state of the cell at the previous moment.

1) The first step of LTSM is mainly to use *forget gate* to determine which information is to be lost from the cell state. It views h_{t-1} and compares the output of the previous moment with the input data x_t of the current moment. After the gate unit function sigmoid to form the *forget gate*, the output of the forget gate can be expressed by Equation (6).

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \tag{6}$$

where f_t represents the output of the forgotten door; W_f represents the weight of the forgetting gate; σ represents the activation function; b_f indicates the offset of the forgetting gate.

2) The second step is to use the input gate to determine which information remains in the cell state, and this process can be divided into two parts. The first part is the input information passing through the gate unit sigmoid function, thus forming the input gate, which calculates the importance of new information to select the values to be discarded or updated, where the output of the input gate can be solved by Equation (7).

$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] + b_i\right) \tag{7}$$

where W_i represents the weight of the input gate; b_i indicates the offset of the input gate.

The other part is that information, through the function tanh, forms the vector of new candidate values to replace values to be discarded. The vector of candidate values can be solved by Equation (8).

$$\widetilde{C}_t = \tanh\left(W_c \cdot [h_{t-1}, x_t] + b_c\right) \tag{8}$$

where $\widetilde{C}_t$ denotes vector of candidate values; W_c represents the weight of the candidate values; b_c indicates the offset of the candidate values.

3) Then, use the relationship between the forget gate, the input gate, the candidate value vector, and the last moment, the cell state at the present moment, as shown in Equation (9).

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \widetilde{C}_t \tag{9}$$

where C_t denotes current moment state of cells.

4) The final step is to determine how much information to output through the output gate. First, the input information is used through a function sigmoid to determine which information needs to be output, and then the cell state is normalized by the function tanh, and finally it is multiplied by the output value of the gate to obtain the output of the cell h_t. The procedure is shown in Equations (10) and (11)

$$o_t = \sigma \left(W_o \cdot [h_{t-1}, x_t] + b_o \right) \tag{10}$$

$$h_t = o_t \cdot \tanh(C_t) \tag{11}$$

where W_o represents the weight of the output gate. b_o indicates the offset of the output gate.

3.2.2. *Determination of the recognition period and update period of the driving cycle condition.* After the LSTM-based recognition model is established, it is necessary to select the recognition period and update period of the driving cycle conditions, which will affect the accuracy of the driving cycle condition recognition model. Firstly, under different recognition period and update period conditions, the four types of standard driving cycle condition data set obtained in Figure 1 of Section 2.4 are divided into sample data with the method shown in Figure 2. Then, the feature parameters of each driving cycle condition segment are extracted. Randomly generate training and test sets in an 8 : 2 ratio. Using the recognition period of the 30 s and the update period of 3 s as examples, the data sets of four types of standard driving cycle conditions are processed separately, and the final results are shown in Table 6.

Table 6. Sample data of various driving cycle conditions

Driving cycle condition category	Sample data sum	Training set data sum	Test set data sum
Type I	351	281	70
Type II	191	153	38
Type III	441	353	88
Type IV	531	425	106
Data sum	1514	1212	302

Normalize the sample data, taking Table 6 as an example, where 1514×1 is used as the input array to identify the model cell, and the output is converted into a category array by the categorical function. Finally, the normalized feature parameters of the training set are used as the input of the model, and the driving cycle condition category is used as the output to train the model. Adam is used as the network optimization algorithm to form a driving cycle state recognition model based on LSTM.

Next, we discuss the selection of identification periods and update periods. In the process of building the driving cycle condition identification strategy, the recognition period ΔT and the update period Δt will also affect the accuracy of the driving cycle condition identification [23]. If the recognition period is too short, the driving cycle condition information is too small; If the recognition period is too large, much useless driving cycle condition information will be added. In addition, if the update period is too small it will lead to large computation, and then need a higher configuration processor; Too large will lead to reduced sensitivity of recognition. Therefore, selecting the appropriate ΔT and Δt can effectively improve the identification accuracy of the driving cycle condition identification model.

In Section 3.2, the driving cycle condition identification model is relatively analyzed under a set recognition period and update period. We selected the 30 s, 60 s, 90 s, 120 s, and 150 s as recognition periods ΔT and 3 s, 5 s, and 10 s as update periods Δt, and divided samples by permutation and combination of different ΔT and Δt. As described in Section 3.2.2, first and second paragraphs, random generated training sets along with test sets, training of the driving cycle condition identification model based on the LSTM algorithm. Finally, through 20 tests on the test set, the recognition effect under different combinations can be obtained. From the recognition results, when the recognition period and update period are 120 s and 5 s, respectively, the recognition accuracy is the highest among all combinations, reaching 99.2073%, as shown in Figure 4. Therefore, the recognition period and update period are finally selected as 120 s and 5 s, respectively.

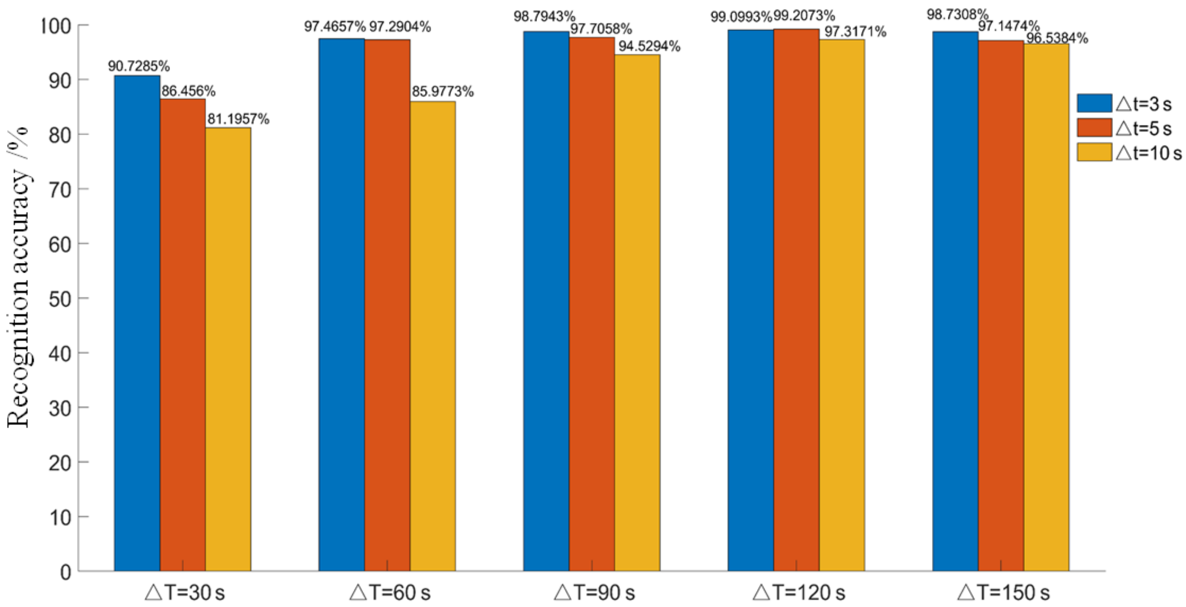


FIGURE 4. Recognition accuracy under different recognition periods and update periods

4. **Analysis of Simulation Results of Driving Cycle Identification Based on LSTM.** In order to evaluate the recognition effect of the driving cycle state recognition model based on LSTM, a total of 164 driving condition test sets were obtained according to the best recognition period 120 s and the best update period 5 s in Section 3.2.2. These 164 test sets are input into the LSTM driving cycle state recognition model, the predicted value obtained is compared with the real value, and the driving cycle condition recognition accuracy is calculated according to Equation (12). The result is shown in Figure 5, and the driving cycle state recognition accuracy obtained under the best recognition period 120 s and the best update period 5 s is 98.7805%.

$$Rate = \frac{N_T}{N_T + N_F} \tag{12}$$

where $Rate$ represents the accuracy of driving cycle condition identification; N_T represents the number of all correctly identified samples in the test set, and N_F represents the number of all incorrectly identified samples in the test set.

The above 164 test sets are composed of four typical driving cycle conditions obtained in Section 2.4. In order to analyze the recognition accuracy of these four types of driving

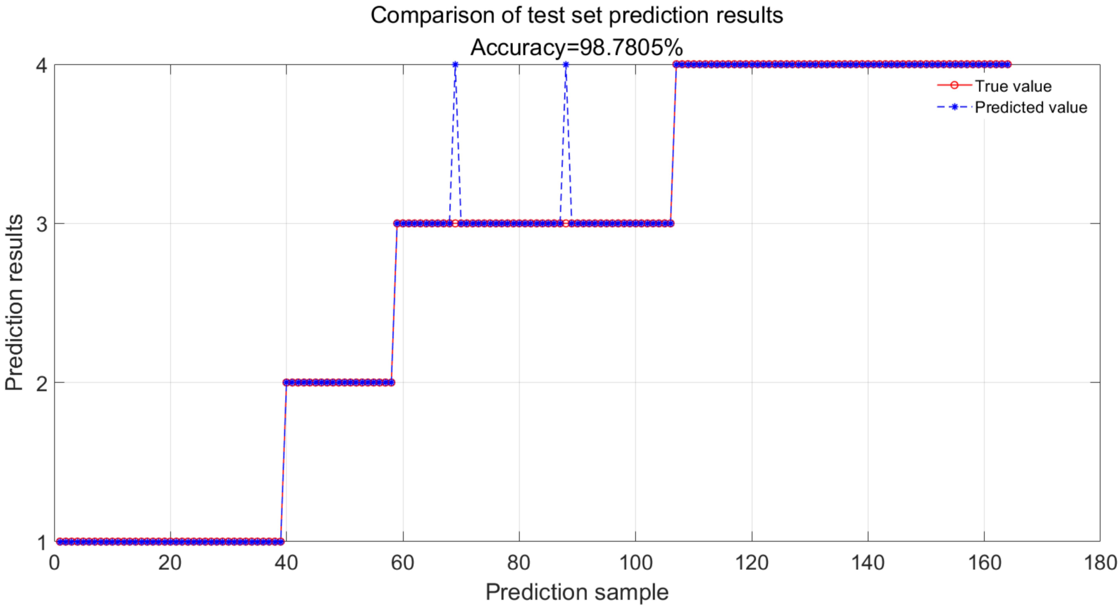
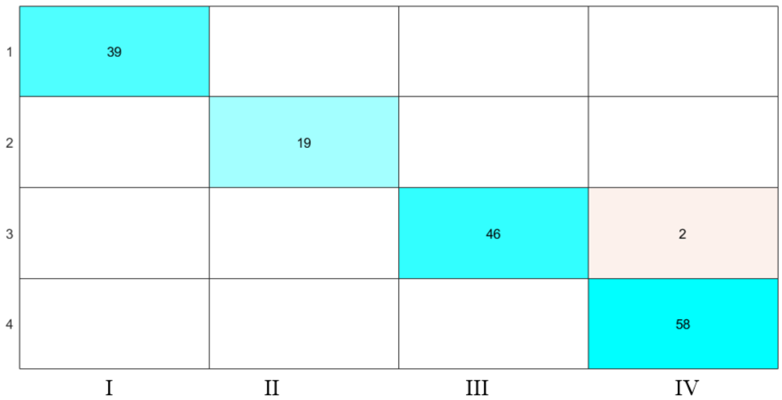
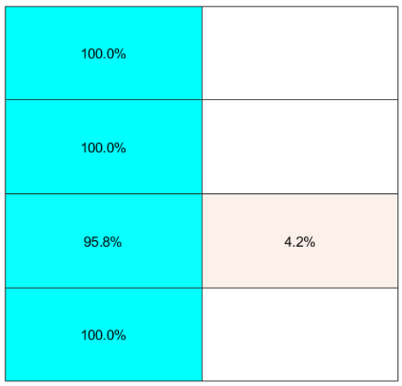


FIGURE 5. Test set identification results



(a) Results I



(b) Results II

FIGURE 6. Confusion matrix of the test set data

cycle conditions under the LSTM recognition model, we write a program to obtain the confusion matrix of the test set data, as shown in Figure 6.

In Figure 6(a), "I, II, III, and IV" represent the types of real driving conditions in the test set, respectively. The data in each row represents the number of test set samples for this typical driving scenario. The ordinates "1, 2, 3, and 4" represent the prediction type results of the driving cycle condition recognition model, respectively. Therefore, the diagonal represents the amount of data where the predicted value coincides with the actual value. The first column in Figure 6(b) shows the accuracy of the driving cycle state recognition, and the second column shows the error rate. As an example of the third behavior of Figure 6(a), 46 samples were correctly identified as the third type of driving cycle conditions, and two samples were incorrectly identified as the fourth type of driving cycle conditions, so the recognition accuracy of the third type test concentrated driving cycle conditions was 95.8%.

In conclusion, from Figure 6, the identification accuracy of each standard driving condition in the test set is 100%, 100%, 95.8%, and 100% under the identification model, respectively From Figure 5, the overall identification accuracy is 98.7805% under this strategy. Therefore, the simulation results show that the LSTM-based driving cycle condition identification strategy can better identify the driving conditions online.

5. **Conclusions.** Driving cycle conditions are the prerequisite for constructing the online identification model of working conditions, so we construct the typical driving cycle datasets with comprehensive road characteristics. The 30 kinds of standard conditions from the standard datasets, considering the urban, suburban, and high-speed driving characteristics, were selected to constitute the original driving cycle database, and we extracted the 15 characteristic parameters and optimized them. Secondly, using a hierarchical clustering algorithm to optimize the original driving cycle database to get four kinds of representative driving conditions, and a condition from each class as the representative of the class was selected. Finally, the typical driving cycle datasets are built.

Based on the theory of the typical driving cycle datasets and LSTM, the online identification model based on LSTM is built. First, the driving cycle condition block is divided, and its characteristic parameters are extracted for driving cycle condition identification and normalized. Then the online identification model based on LSTM is constructed, and the recognition effect is verified. Finally, different recognition periods and update periods are combined to analyze the impact on recognition accuracy under different combinations to determine the best combination of recognition periods and update periods. The simulation results show that the LSTM identification model based online can better identify the driving cycle conditions, which can lay a certain theoretical foundation for the design and control strategy of new energy vehicles.

The next step is to research the following aspects. 1) This paper's original driving cycle database is based on the international standard driving cycle condition. In the next step, GPS and differential equipment are used to collect and analyze the driving cycle condition data to build a road driving condition that conforms to the actual situation in China. 2) Next, based on the online identification results of driving cycle conditions, the energy control strategy of hybrid electric vehicles will be constructed, which lays the foundation for the engineering application of an intelligent algorithm of the control strategy.

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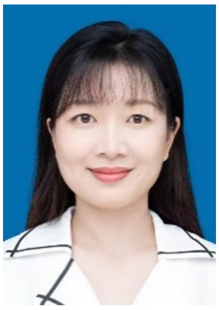
Author Biography



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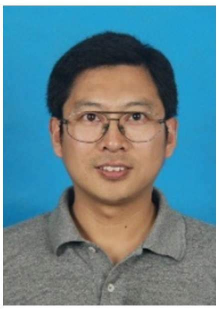

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