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Second Optimization Method of Neural Network Driving Condition Identification Based on the Genetic Algorithm

Shipeng Li[1], Ruijun Liu[1], Dapai Shi[2*], Jinlong Yang[1], Junjie Guo[2] and Qingling Cai[2]
[1]School of Transportation and Vehicle Engineering, Shandong University of Technology, Shandong, Zibo, Zhangdian, 255049, China.
[2]School of Automobile and Traffic Engineering, Hubei University of Arts and Science, Hubei, Xiangyang, Xiangcheng, 441000, China.
[*]Corresponding author email id: sdapai@163.com@sdut.edu.cn

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Abstract **– In order to solve the problem that the low recognition rate of the driving condition reduces the control effect of the whole vehicle energy control strategy, this paper proposes an intelligent identification method of the driving condition which uses a genetic algorithm (GA) to optimize the back propagation neural network (BPNN) intelligent identification of driving conditions. First, 21 typical driving conditions are classified according to the dimension reduction characteristic values and the comprehensive driving condition is constructed. Second, the typical driving condition identification model is established by the K-means clustering and simulated. Then, the K-means condition identification model is optimized by the BPNN method and the BPNN condition identification model are simulated. Finally, the genetic algorithm is used to optimal the BPNN condition identification model, and the second optimization model of the BPNN condition identification (GA-BPNN) is established and simulated in the MATLAB environment. The main contribution of the paper is that GA-BPNN condition identification can accurately identify future driving conditions. Results show that compared with the traditional K-means clustering method and BPNN intelligent identification method, the GA-BPNN driving condition intelligent identification method can further improve the condition identification accuracy, and the driving conditions recognition accuracy reaches 93%.**

Keywords **– Plug-in Hybrid Electric Vehicle, Driving Cycle Prediction, Energy Management Strategy, Equivalent Fuel Consumption Minimization.**

I. Introduction

At present, the logic threshold energy control strategy of PHEVs is mainly based on the parameters of current vehicle demand power, driving speed, power battery SOC, etc. The logic threshold energy control strategy can improve the efficiency of plug-in hybrid vehicles (PHEVs) under certain driving conditions, but it cannot guarantee the minimum fuel consumption when the vehicle runs under actual driving conditions [1-2]. The actual driving conditions will change with the changing driving habits, driving routes, traffic conditions and road conditions. Therefore, the design of energy control strategy should consider the road condition information of vehicles in the future, and condition identification technology is one of the effective means to obtain the information of future driving conditions [3].

The basic principles of driving condition identification are to classify the typical driving conditions, select the representative driving conditions to build comprehensive driving conditions, and then use different identification methods to identify the current driving conditions of the vehicle, such as clustering and neural network. The selected comprehensive driving conditions are compared with the selected driving conditions, in order to identify the type of the current operating conditions belong [4-5]. Since the identification accuracy of the future driving condition information will seriously affect the control effect of the control strategy, cluster analysis, neural network, dynamic programming, intelligent control and other methods can be used to predict and identify the future vehicle driving condition information [6-8]. Shi et al of Hefei University of Technology used the K-means clustering method to identify and classify the road conditions in the city based on the dimensionality reduction of the characteristic parameters of the driving conditions. The accuracy of the classification results can be meet the requirements [9]. Yin et al selected four typical urban driving conditions, used principal component analysis and K-means clustering method to filter out four representative parameters such as average speed, and finally identified and classified the real-time operating conditions through the LVQ neural network. The results prove the high efficiency of the recognition accuracy [10]. After denoising and filtering the collected signals, Zhang et al used principal component analysis to reduce the dimensionality of the collected data. Finally, based on the obtained data, the driving condition samples are established, and the KNN algorithm is used to train and classify them, obtaining better results [11]. Zhang et al proposed an adaptive minimum equivalent fuel consumption strategy to improve the energy management strategy of hybrid heavy-duty vehicles. Six typical driving conditions of hybrid heavy-duty vehicles are obtained through hierarchical clustering algorithm, and a driving condition recognition algorithm based on neural network is proposed [12].

Based on the above analysis of the driving condition identification method, this paper firstly uses principal component analysis method to reduce the dimension of the driving condition characteristic parameters and establish a comprehensive driving condition. Secondly, the K-means clustering identification model is established by the K-means clustering identification method, and is simulated to verify its recognition accuracy. Then, the BP driving condition recognition model is used established by the BPNN intelligent algorithm and simulated to verify its recognition accuracy. Finally, the GA-BPNN intelligent recognition model of the driving condition is established by the genetic algorithm and is simulated to verify its driving condition recognition accuracy. Meanwhile, the recognition results three different driving condition recognition methods are summarized and analyzed. Results show that compared with the K-means clustering identifications and BP neural network intelligent algorithm, the GA-BPNN driving condition intelligent recognition can more accurately identify the condition identification accuracy.

II. Construction of Driving Conditions

During the actual driving process, the vehicle will drive under the complex road conditions, such as cities, villages and highways. Besides, the speed of the vehicle will also vary greatly with the time under various driving conditions. In order to construct a comprehensive driving condition, multiple kinematic characteristic parameters are selected to characterize each typical driving condition, and the principal component analysis method is used to reduce the dimensionality. Feature parameters, several feature parameters with low correlation are obtained as variables for the classification of typical driving conditions [13].

Considering the comprehensiveness of comprehensive driving conditions, 21 typical driving conditions are classified by the K-means clustering method. Some characteristics of these 21 typical driving conditions are shown in Table 1.

It can be seen from Table 1 that 21 typical driving conditions are characterized by nine characteristic parameters. The nine characteristic parameters are the maximum driving speed v_{max}, the average driving speed v_{avg}, the maximum acceleration $a_{acc\_\max}$, the average acceleration a_{acc_avg}, the maximum deceleration $a_{dcc\_\max}$, and the average deceleration a_{dcc_avg}, Total stroke S, idling time T_{idle} and number of stops I_{stop}. Although more characteristic parameters of each driving condition will improve the accuracy of the identification, too many feature parameters will increase the workload of driving condition identification, which leads to poor real-time performance of condition recognition. Considering the impact on the real-time performance of driving condition recognition, the main component analysis method is used to reduce the dimension of the 21 driving conditions by the SPSS software.

Table 1. 21 Characteristic parameters of typical cycle conditions.

Driving Condition	v_{max}	v_{avg}	a_{acc_max}	a_{acc_avg}	a_{dcc_max}	a_{dcc_avg}	S	T_{idle}	I_{stop}
JPN1015	69.97	22.68	0.79	0.57	-0.83	-0.65	4.16	215	7
ARB02	129.23	70.04	3.53	0.66	-3.62	-0.7	31.91	123	19
ARTERIAL	64.37	39.71	1.07	0.6	-2.01	-1.79	3.22	48	4
CBDTRUCK	32.19	14.86	0.36	0.29	-0.63	-0.56	3.51	159	14
COMMUTER	88.51	70.28	1.03	0.28	-2.01	-1.89	6.44	40	1
ECE_EUDC	120	32.1	1.06	0.54	-1.39	-0.79	10.93	339	13
FTP	91.25	25.82	1.48	0.51	-1.48	-0.58	17.77	361	22
HL07	128.75	85.74	3.58	1.29	-2.55	-0.79	10.05	41	2
HWFET	96.4	77.58	1.43	0.19	-1.48	-0.22	16.51	6	1
LA92	108.15	39.6	3.08	0.67	-3.93	-0.75	15.8	234	16
MANHATTAN	40.72	10.98	2.06	0.54	-2.5	-0.67	3.32	394	20
NEDC	120	33.21	1.06	0.54	-1.39	-0.79	10.93	298	13
NYCC	44.58	11.41	2.68	0.62	-2.64	-0.61	1.9	210	18
NYCCOMP	87.94	14.1	4.11	0.47	-3.88	-0.54	4.03	341	19
NurembergR36	53.7	14.33	1.88	0.58	-2.11	-0.55	4.32	334	24
SC03	88.19	34.51	2.28	0.5	-2.73	-0.6	5.76	117	6
UDDS	91.25	31.51	1.48	0.5	-1.48	-0.58	11.99	259	17
US06	129.23	77.2	3.76	0.67	-3.08	-0.73	12.89	45	5
WVUCTIY	57.65	13.59	1.14	0.3	-3.24	-0.4	5.32	427	14
WVUINTER	97.74	54.75	1.42	0.2	-1.82	-0.21	24.96	153	9
WVUSUB	72.1	25.87	1.29	0.33	-2.16	-0.42	11.97	420	9

The correlation coefficient between each characteristic parameter is shown in Table 2.

Table 2. Correlation coefficient of characteristic parameters.

Characteristic Parameters	v_{max}	v_{avg}	a_{acc_max}	a_{acc_avg}	a_{dcc_max}	a_{dcc_avg}	S	T_{idle}	I_{stop}
v_{max}	1.000	0.726	0.437	0.383	-0.237	-0.040	0.651	-0.332	-0.287

Characteristic Parameters	v_{max}	v_{avg}	a_{acc_max}	a_{acc_avg}	a_{dcc_max}	a_{dcc_avg}	S	T_{idle}	I_{stop}
v_{avg}	0.726	1.000	0.310	0.264	-0.114	-0.225	0.552	-0.779	-0.661
a_{acc_max}	0.437	0.310	1.000	0.575	-0.812	0.117	0.218	-0.168	0.145
a_{acc_avg}	0.383	0.264	0.575	1.000	-0.287	-0.180	-0.036	-.181	-0.002
a_{dcc_max}	-0.237	-0.114	-0.812	-0.287	1.000	-0.013	-0.153	-0.048	-0.191
a_{dcc_avg}	-0.040	-0.225	0.117	-0.180	-0.013	1.000	0.274	0.378	0.347
S	0.651	0.552	0.218	-0.036	-0.153	0.274	1.000	-0.183	0.033
T_{idle}	-0.332	-0.779	-0.168	-0.181	-0.048	0.378	-0.183	1.000	0.707
I_{stop}	-0.287	-0.661	0.145	-0.002	-0.191	0.347	0.033	0.707	1.000

When the correlation coefficient is between 0.6 and 0.8, the two variables are strongly correlated. At this time, one variable is selected as a representative. According to the correlation between the various characteristic parameters presented in the Table 2 a total of four selections including the maximum driving speed, the maximum acceleration, the average acceleration and the average deceleration are selected under the premise of ensuring the accuracy and real-time of driving conditions. The feature parameters are the result of dimensionality reduction processing. The four selected characteristic parameters are used to carry out systematic clustering analysis under the 21 typical driving conditions. In the clustering process, the distance between different individuals is calculated by "square Euclidean distance" formula as in (1) for classification.

$$P(i,j)=\left|x_i - x_j\right| = \sum_{m=1}^{4}(x_{im}-x_{jm})^2 \quad i\neq j \bigcap i,j\in Z^+ \bigcap i,j\in[1,21] \tag{1}$$

Where, i and j represent different individuals, and m represents a variable.

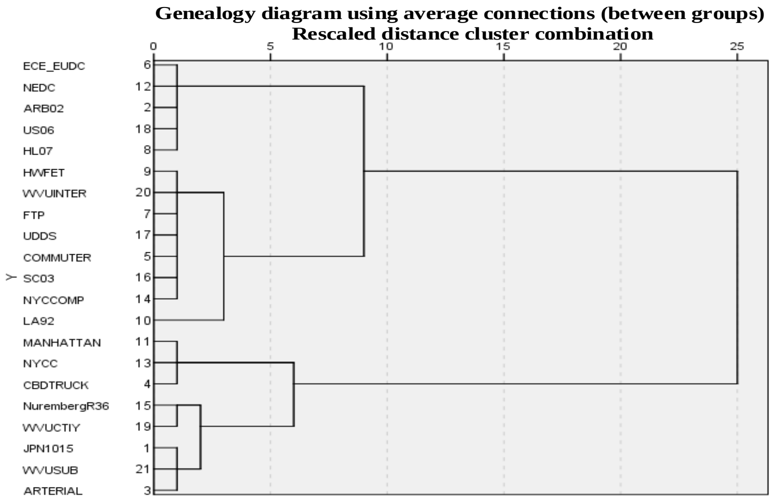

Fig. 1. Genealogy diagram of 21 typical driving conditions.

After systematic clustering, the pedigree diagram of 21 typical driving conditions is shown in Figure 1.

Table 3. Classification results of 21 driving conditions.

Driving Condition Classification	Driving Condition	Similar Conditions
First category	CBDTRUCK, MANHATTAN, NYCC	Congestion conditions
Second category	JPN1015, ARTERIAL, NurembergR36, WVUCITY, WVUSUB	City conditions
The third category	FTP, UDDS, COMMUTER, SC03, NYCCOMP, HWFET, LA92, WVUINTER	Fast driving condition
The fourth category	ARB02, ECE_EUDC, HL07, NEDC, US06	High-speed driving conditions

It can be seen from the Figure 1 that with the reduction of the redirection, the classification of 21 typical driving conditions becomes more detailed. In order to ensure the similarity of the driving conditions within the group and the accuracy of the clustering after the grouping, the paper will select a reset ratio of 5 and divide all the driving conditions into four categories. After analyzing the data of each type of driving condition, the four types of driving conditions are named as congestion driving condition, urban driving condition, fast driving condition and high-speed driving condition respectively. The classification results of 21 typical driving conditions are shown in Table 3.

In order to construct a comprehensive driving conditions, the representative typical driving conditions are selected as sub-conditions from four kinds of driving conditions. After comparative analysis of each typical driving condition, NurembergR36 in urban conditions, HWFET in fast conditions, NYCC in congestion conditions, US06 in high-speed conditions, and UDDS in fast conditions are selected, a total of five A typical driving conditions is connected to construct a comprehensive driving conditions, as shown in Figure 2.

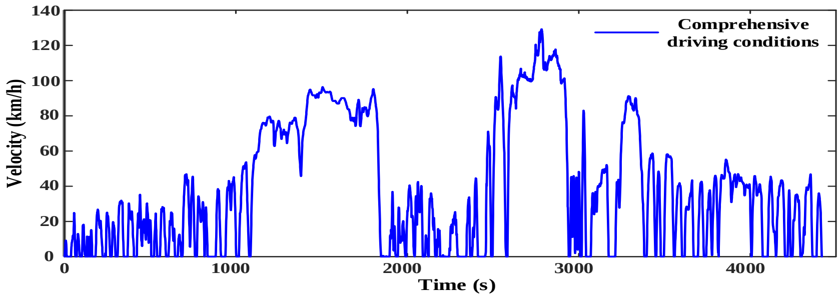

Fig. 2. Comprehensive driving conditions

III. Establishment and Verification of K-Means Clustering Recognition Model

During the process of identifying driving conditions, using traditional K-means clustering identification is a simple and easy method [14]. K-means algorithm tries to solve the clustering problem by optimizing the given index [15]. The basic driving principle of this method is to determine k initial cluster centers and iteration times. At the beginning of iteration, the distance between each point in the data set and the cluster center is determined by Euclidean distance calculation formula as in (2), and then each point and its nearest cluster center are classified as a class, and then the average value of this class of points is taken as the cluster center at the beginning of the next iteration, and this process is repeatedly cycled until the accuracy requirement is met or the iteration is controlled according to the maximum iteration times [16].

$$P(i,j)=\left|x_i - x_j\right| = \sqrt{\sum_{m=1}^{4}(x_{im}-x_{jm})^2} \quad i \neq j \bigcap i, j \in Z^+ \bigcap i \tag{2}$$

Where, i and j represent different individuals, and m represents a variable.

Before using K-means for cluster recognition, the K-means clustering function is firstly used in SPSS software, the cluster center to 4 and the number of iterations to 2 are set and then the final cluster center of 21 typical driving conditions are determined, as shown in Table 4.

Table 4. The final Cluster Centers of 21 Driving Conditions.

Category	1	2	3	4
Maximum driving speed	93.68	125.44	63.56	39.16
Maximum acceleration	2.04	2.60	1.23	1.70
Average acceleration	0.42	0.74	0.48	0.48
Average deceleration	-0.67	-0.76	-0.76	-0.61

After determining the final cluster center for cluster identification, the integrated driving conditions established above are taken as a test sample. Before the condition identification, the selected test samples need to be processed. The operating time of the comprehensive driving condition is 4418 seconds. If this operating condition is used directly for operating condition identification, the operating cycle of this operating condition is too long and cannot meet the identification needs of actual road conditions. Compared with the recognition accuracy of driving conditions in different time intervals, it is ensured that sufficient useful road condition information can be extracted in each time interval and the recognition results can meet real-time performance and reduce frequent shifting phenomena. A time interval of 120 seconds will be selected to extract data from the 4418 second comprehensive driving condition [17].

After completing the above work, the recognition program of the K-means driving condition clustering is wrote by the MATLAB soft. The comprehensive driving conditions are identified at intervals of 120 seconds for each driving condition. The congestion driving condition, urban driving condition, fast speed operating conditions and high-speed operating conditions are respectively represented by 1, 2, 3, and 4 in the identification results. Recognition results and the recognition errors of the comprehensive driving condition are shown in Figure 3 and Figure 4 which is recognized by the K-means clustering method.

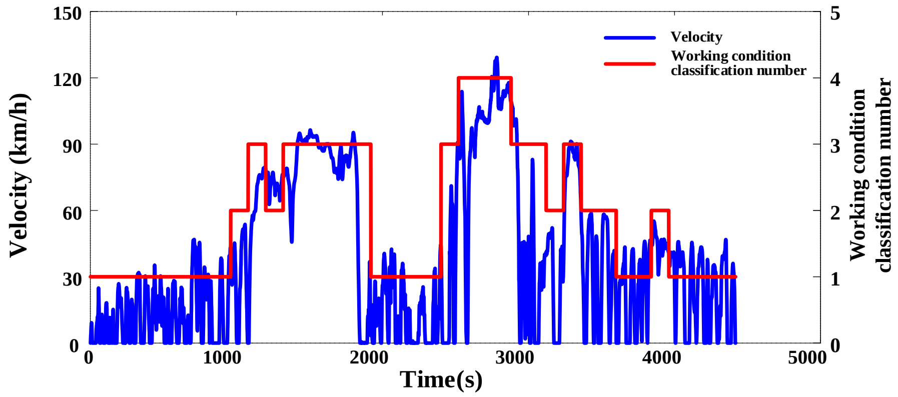

Fig. 3. Driving condition recognition result based on K-means clustering

Although the recognition rate of K-means clustering recognition method is faster for comprehensive driving conditions, it can be seen from the figure that there are some errors in the identification of driving conditions. Compared with actual requirements, the accuracy of driving condition recognition is low and maintained above 60%. In order to optimize the accuracy of driving condition recognition, the following will propose a better method to recognize vehicle driving conditions.

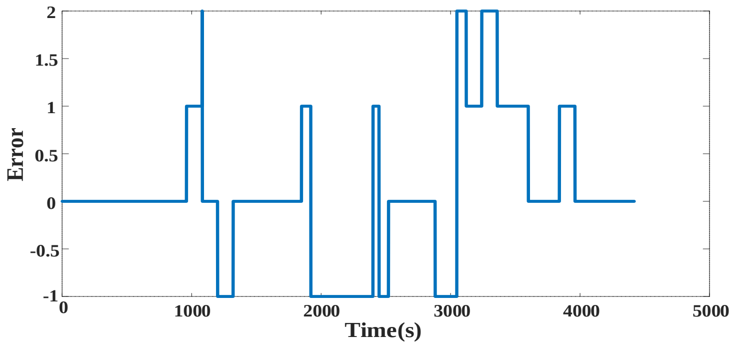

Fig. 4. Driving condition recognition error based on K-means.

IV. Establishment and Verification of BPNN Driving Condition Recognition Model

In order to further improve the accuracy of driving condition recognition, the method of BP neural network will be used to identify the comprehensive driving conditions. The basic idea of the BP neural network algorithm is that the learning process includes two stages of signal feed forward propagation and error feed forward propagation. It is roughly composed of input layer, hidden layer and output layer. The hidden layer can be composed of multiple layers [18-19]. In the phase of signal forward propagation, the input signal starts from the input layer and is transmitted layer by layer to the output layer. If the actual output signal is inconsistent with the expected output signal, the algorithm will move to the error feed forward propagation stage. The error is transmitted from the output layer to the input layer and distributed to all units in each layer. The error signal is the basis for correcting unit weights and deviations [20]. Figure 5 shows the topological structure of BPNN.

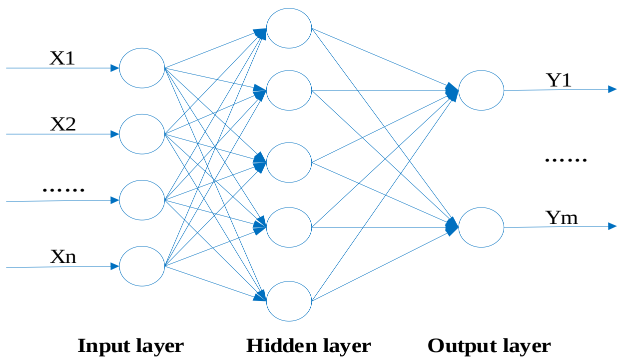

Fig. 5. BPNN topology.

As can be seen from the above figure, the BPNN is similar to a non-linear function. The input of the input layer is regarded as the independent variable, the output of the output layer is regarded as the dependent variable, and the hidden layer is regarded as the mapping relationship between the independent variable and the dependent variable [21].

(1) Network initialization. According to the number of selected feature parameters, set the input layer neuron to n. hidden layer neuron to l, and output layer neuron to m. In this step, the weights and thresholds of each layer are initialized. The neuron activation function uses the default function $f(x)=1/(1+e^{-x})$, x is the input signal of each neuron in the input layer.

(2) Use formula as in (3) to calculate the output of the hidden layer.

$$H_j = f(\sum_{i=1}^{n}\omega_{ij} - a_j) \qquad j = 1,2,\dots,l \tag{3}$$

Where, H_j is the output of each hidden layer neuron, a_j is the threshold of each hidden layer neuron, and ω_{ij} is the weight between the input layer neuron and the hidden layer neuron.

(3) Use formula as in (4) to calculate the output of the output layer.

$$O_p = \sum_{j=1}^{l} H_j \omega_{jp} - b_p \qquad p = 1,\ 2,\ m. \tag{4}$$

Where, O_p is the output of each output layer neuron, b_p is the threshold of each output layer neuron, and ω_{jp} is the weight between the hidden layer neuron and the output layer neuron.

(4) Calculate the network output error by formula as in (5).

$$E_p = Q_p - O_p \tag{5}$$

(5) Update weights and thresholds by the formulas as in (6) and (7).

$$\omega_{ij} = \omega_{ij} + LH_j(1-H_j)x(i)\sum_{p=1}^{m}\omega_{jp}E_p \tag{6}$$

$$\omega_{jp} = \omega_{jp} + LH_j E_p \omega_{jp} \tag{7}$$

The L in the above formula represents the learning rate of the network, and the default value of the network is 0.01.

(6) If the actual output does not meet the expected output or does not meet the preset iteration stop standard, return to the second step to continue this cycle.

Through the above analysis, the program of BPNN driving condition recognition is established by MATLAB. Before driving condition training of BPNN, it is necessary to determine a suitable training set, which will affect the iteration times and training accuracy of BPNN. In this paper, from the selected four representative driving conditions, 100 samples are randomly selected according to the time period of 120 seconds to represent each type of driving condition, and four characteristic parameter values under 400 samples are selected as the sample set for BPNN training, and the selected data are normalized. According to the number of characteristic parameters, the input layer neurons of BPNN are determined to be 4; Because the four driving conditions represented by the output vector can be transformed into index vectors, one neuron in the output layer is determined; Considering that the number of hidden layer neurons will affect the recognition efficiency and accuracy of BPNN, the number of hidden layer neurons is determined to be 5. The recognition results and error percentage of driving conditions using BPNN are shown in Figure 6 and Figure 7 respectively.

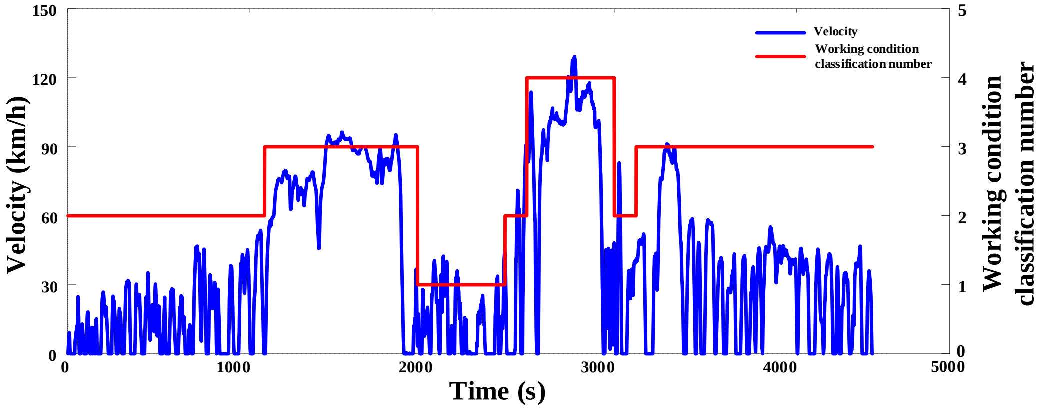

Fig. 6. Neural network driving condition recognition result graph.

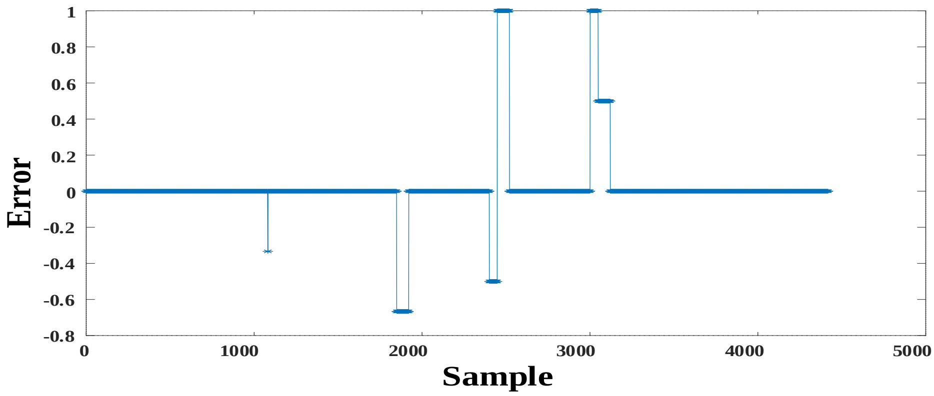

Fig. 7. Percentage graph of neural network driving condition recognition error.

It can be seen from Figure 6 and Figure 7 that the driving condition recognition based on BPNN takes a little longer, and the accuracy of the condition recognition is significantly improved compared with the K-means clustering recognition method. Although there are errors in the recognition of some driving conditions, the overall recognition accuracy of driving conditions is about 86%, which can meet the needs of the recognition accuracy of vehicles in the actual driving process.

V. Establishment and Verification of Intelligent Identification Model for Secondary Optimization Conditions

In order to further improve the accuracy of the BPNN's recognition, the genetic algorithm is used to optimize the BPNN, so as to achieve the purpose of improving the driving condition recognition accuracy. Genetic algorithm is a method of parallel and random search for the optimal solution of the target formed by simulating the mechanism of biological genetic evolution. The genetic algorithm roughly includes three processes which are the selection operation, crossover operation and mutation operation [22-23]. Genetic algorithm optimization BPNN includes three parts: Confirmation of BPNN structure for driving condition recognition, Genetic algorithm optimization of BPNN, and Using optimized BPNN for driving condition recognition and classification [24-25].

The structure determination of BPNN for driving condition identification is the preparatory work for the whole genetic algorithm to optimize BPNN (GA-BPNN). This step is used to determine the individual length of genetic algorithm first. According to the selected typical driving conditions, the BPNN has a 4-5-1 structure, that is, it contains four input layer neurons, five hidden layer neurons and one output layer neuron, thus determining that the individual length of the population is $4\times5+5\times1+5+1=31$. The following will introduce the specific steps of genetic algorithm:

(1) The genetic algorithm population is initialized according to the individual length. Each individual population contains the ownership value and threshold value of the BPNN. Initialize the population to generate a specific number of initialized individuals as the initial point of the next iteration. In this process, all individuals in the population are encoded by the "real number method" [26].

(2) Selection of fitness value. The fitness value function determined according to the weights and thresholds in the BPNN can calculate the fitness value of each individual for subsequent selection operations. The calculation formula is shown in (8).

$$F = k(\sum_{i=1}^{n} abs(y_i - o_i)) \tag{8}$$

Where k is the coefficient, y is the expected output, o is the actual output, and n is the number of nodes.

(3) Select an action. The proportion of fitness value represents the probability of being selected by each individual, and the calculation formula of probability is shown in (9).

$$p_i = \frac{k / F}{\sum_{j=1}^{N} (k / F_j)} \tag{9}$$

The N in the above formula represents the population size.

After determining the probability of the fitness value of each individual, the “roulette” method is used to generate a random number between 0 and 1 to determine the number of times each individual is selected.

(4) Cross operation. The crossover operation is a random process. First, two individuals in the population are randomly selected for pairing, and then a certain locus position is randomly selected on each pair of individuals as the crossover operation. The specific operation formula is shown in (10).

$$\left.\begin{aligned} c_1 &= p_1 \times a + p_2 \times (1-a) \\ c_2 &= p_1 \times (1-a) + p_2 \times a \end{aligned}\right\} \tag{10}$$

Where, p represents the original individual, c represents the new individual, and a is the crossover probability.

(5) Mutation operation. Perform mutation operation on the $j-\text{th}$ gene a_{ij} of the $i-\text{th}$ individual, as shown in (11).

$$a_{ij} = \begin{cases} a_{ij} + (a_{ij} - a_{\max}) * r_2 (1 - g / G_{\max})^2 & r > 0.5 \\ a_{ij} + (a_{\min} - a_{ij}) * r_2 (1 - g / G_{\max})^2 & r \le 0.5 \end{cases} \tag{11}$$

Where $a_{\max}$ and $a_{\min}$ respectively represent the upper and lower limits of gene a, G represents the number of evolution, and r represents a random number between 0 and 1.

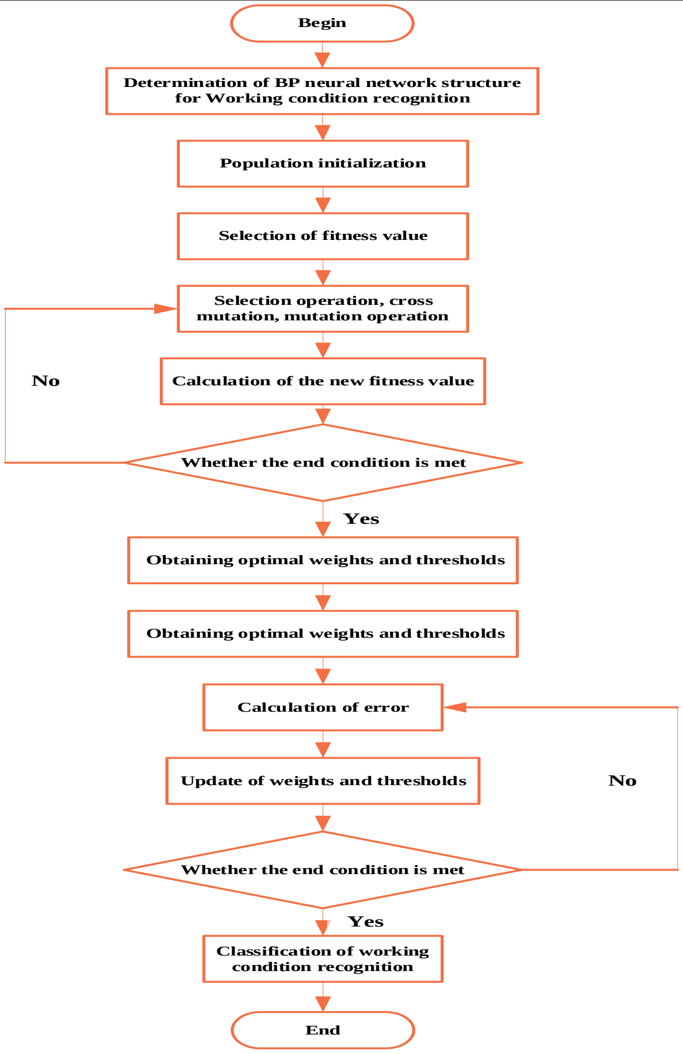

Fig. 8. Recognition process of the optimized BPNN's driving condition based on Genetic Algorithm.

After the above analysis of the genetic algorithm, it is determined that the driving condition identification process based on the genetic algorithm to optimize the BPNN is shown in Figure 8.

According to the Figure 8, the genetic algorithm optimization program was written by the MATLAB software and embedded into the design BPNN. Based on the GA-BPNN model, the driving condition recognition results and the driving condition recognition error percentage are shown in Figure 9 and Figure 10.

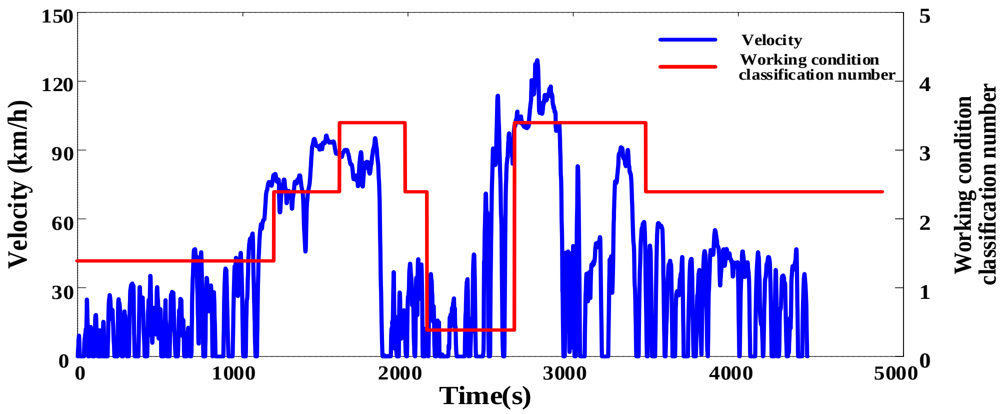

Fig. 9. Recognition results of neural network driving conditions based on genetic algorithm.

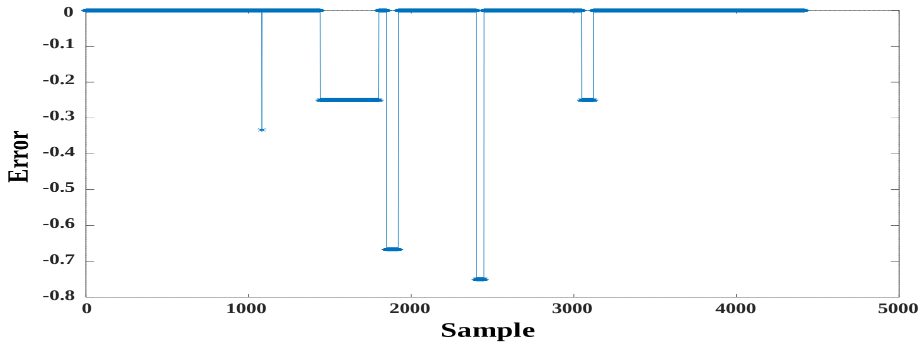

Fig. 10. Percentage of driving condition recognition error.

When the genetic algorithm iterated to the nineteenth time, the GA-BPNN is completed. It can be seen from the above figure that the GA-BPNN algorithm has further improved the recognition accuracy of driving conditions, which can reach about 93%. Therefore, the GA-BPNN driving condition identification model can meet the needs of identifying the actual road conditions during driving.

VI. CONCLUSION

In this paper, the principal component analysis method is used to reduce the nine characteristic parameters of the driving condition. Four representative characteristic parameters of maximum driving speed, maximum acceleration, average acceleration and average deceleration are selected, and the K-means clustering method is used to construct the comprehensive driving condition. K-means clustering identification method, BPNN intelligent identification method and GA-BPNN intelligent identification method are used to establish corresponding driving condition identification models, and verify the accuracy of driving condition identification models under comprehensive driving conditions. Through the simulation and comparison analysis of the three driving conditions identification modeling results, the following conclusions are obtained:

(1) Compared with the K-means recognition method, the BPNN driving condition recognition method has a greater improvement in accuracy.

(2) Although the accuracy of BPNN recognition is slightly improved, the accuracy of the GA-BPNN recognition has the highest accuracy.

(3) The BPNN identification mistakenly identifies the urban driving condition as the congestion condition, and the GA-BPNN can realize the correct identification of the driving condition.

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REFERENCES

[1] L.M. NIU, L.J. Ye, H.Y. Yang, Y.K. Wang, “Study on power matching strategy of phev based on fuzzy recognition of driving cycles,” Mechanical Engineering Journal, 4, 1, 16-00202-16-00202.
[2] Jian. W, “Fuzzy control strategy of parallel HEV based on driving cycle recognition,” IEEE Power Electronics & Motion Control Conference.
[3] CM. Martínez, X. Hu, D. Cao, E. Velenis, M. Wellers, “Energy management in plug-in hybrid electric vehicles: recent progress and a connected vehicles perspective,” IEEE Transactions on Vehicular Technology, 66, 6, 4534-4549.
[4] X. Zhang, L. Zheng, “Intelligent energy control strategy for plug-in hybrid electric vehicle based on driving condition recognition,” IPP-

-TA: Quarterly Journal of Indian Pulp and Paper Technical Association, 30, 5, 682-692.
[5] C. Ma, K. Yang, L.D. Miao, M.Q. Chen, S. Gao, "Development of driving condition classification based adaptive optimal control strategy for PHEV," International Journal of Electric and Hybrid Vehicles, 11, 3, 235-.
[6] M. G. Fotouhi, "Traffic condition recognition using the k-means clustering method," Scientia Iranica, 18, 4, 930-937.
[7] T. Liu, X. Tang, J. Chen, H. Wang, Y. Yang, "Transferred energy management strategies for hybrid electric vehicles based on driving conditions recognition," 2020 IEEE Vehicle Power and Propulsion Conference (VPPC), 2020, 1-6.
[8] Y. Zhou, A. Ravey, Péra. Marie-Cecile, "A survey on driving prediction techniques for predictive energy management of plug-in hybrid electric vehicles," Journal of Power Sources, 412, 1, 480-495.
[9] B. Liu, S. Qin, H. Lin, D. Qiu, "A study on the construction of Hefei urban driving cycle for passenger vehicle," IFAC-Papers On-Line, 51, 31, 854-858.
[10] A. D. Yin, T. Jiang, "Research on control strategy of Plug-in hybrid electric vehicle based on driving cycle recognition by LVQ algorithm," Vehicle & Power Technology, 2, 6, 1-6.
[11] Z. Y. Zhang, J. Z. Hui, Z. Shi, S. H. Gao, X. H. Zhang, H. W. Fan, "Cycle Condition Identification of Loader Based on Optimized KNN Algorithm," IEEE Access, 8, 69532-69542.
[12] P. Zhang, X.P. Wu, C.Q. Du, H. M. Xu, H.W. Wang, "Adaptive equivalent consumption minimization strategy for hybrid heavy-duty truck based on driving condition recognition and parameter optimization," Energies, 13, 20, 5407.
[13] Y.B. Yu, J.Y. Jiang, P. Y.,Wang, J. K. Li, "A-ECMS for phev based on real-time driving cycle prediction and personalized travel characteristics," Mathematical Biosciences and Engineering, 17, 6, 6310-6341.
[14] J. Chen, X. Qi, L. Chen, F. Chen, G. Cheng, "Quantum-inspired ant lion optimized hybrid k-means for cluster analysis and intrusion detection," Knowledge-Based Systems, 203, 106167.
[15] Y. L. Zhang, N. Liu, S. P. Wang, "A differential privacy protecting k-means clustering algorithm based on contour coefficients," PLoS ONE, 13, 11, e0206832.
[16] T. Zang, Z. He, F. Ling, W. Yan, Q. Qian, "Adaptive method for harmonic contribution assessment based on hierarchical k-means clustering and bayesian partial least squares regression," Iet Generation Transmission & Distribution, 10, 13, 3220-3227.
[17] P. Pisu, G. Rizzoni, "A comparative study of supervisory control strategies for hybrid electric vehicles. IEEE Transactions on Control Systems Technology," 15, 3, 506-518.
[18] Y. Ou, Z. Zhou, G. Q. Tang, H. W. Sun, X. Z. Zhang, "Control strategy for plug-in hybrid electric vehicle based on self-adaptive road condition," China Journal of Highway and Transport. 29, 09, 152-158
[19] L. Zhang, F. L. Wang, T. Sun, B. Xu, "A constrained optimization method based on bp neural network," Neural Computing & Applications, 29, 2, 413-421.
[20] G. J. Chen, S. Hou, B. Yan, R. P. Guo, G. X. Sun, "Vibration prediction of hardened steel in precision cutting based on bp neural network," Journal of Industrial and Production Engineering, 37, 6, 1-8.
[21] Z. Yao, S. Lu, Y. Li, X. Yi, "Cycle life prediction of lithium ion battery based on DE-BP neural network," IEEE 2019 International Conference on Sensing, Diagnostics, Prognostics, and Control (SDPC), 137-141.
[22] L. Jing, M. A. Ashraf, "Face recognition method based on ga-bp neural network algorithm," Open Physics, 16, 1, 1056-1065.
[23] S. M. Cho, W. J. Chung, "Minimization of surface deflection in rectangular embossing using automatic training of artificial neural network and genetic algorithm," International Journal of Automotive Technology, 20, S1, 57-66.
[24] B. H. Zheng, "Material procedure quality forecast based on genetic BP neural network," Modern Physics Letters B, 31, 2, 1740080.
[25] Q. Jiang, R. Huang, Y. Huang, S. Chen, C. Liu, "Application of bp neural network based on genetic algorithm optimization in evaluation of power grid investment risk," IEEE Access, 7, 154827-154835.
[26] R. Song, X. Zhang, C. Zhou, J Liu, J. He, "Predicting TEC in China based on the neural networks optimized by genetic algorithm," Advances in Space Research, 62, 4, 745-759.

AUTHOR'S PROFILE

First Author
Shipeng Li, Male, Master in reading, School of Transportation and Vehicle Engineering, Shandong University of Technology, 255049, Zhangdian district, Zibo city, Shandong province, China.

Second Author
Ruijun Liu, Male, Associate professor, School of Transportation and Vehicle Engineering, Shandong University of Technology, 255049, Zhangdian district, Zibo city, Shandong province, China.

Third Author
Dapai Shi, Male, Associate Professor, Hubei Key Laboratory of Power System Design and Test for Electrical Vehicle, Hubei University of Arts and Science, Xiangyang, 435003, China.

Fourth Author
Jinlong Yang, Male, Master in reading, School of Transportation and Vehicle Engineering, Shandong University of Technology, 255049, Zhangdian district, Zibo city, Shandong province, China.

Fifth Author
Junjie Guo, Male, Master in reading, Hubei Key Laboratory of Power System Design and Test for Electrical Vehicle, Hubei University of Arts and Science, Xiangyang, 435003, China.

Sixth Author
Qingling Cai, Female, Master in reading, Hubei Key Laboratory of Power System Design and Test for Electrical Vehicle, Hubei University of Arts and Science, Xiangyang, 435003, China.