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Driving Pattern Recognition of Hybrid Electric Vehicles Based on Multi-hierarchical Fuzzy Comprehensive Evaluation

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Abstract

Energy management strategy is a key technology which affects the fuel economy of hybrid electric vehicles (HEVs), which is greatly affected by the complex driving environment of vehicles, and further research is needed in the aspect of comprehensive consideration of vehicle driving pattern. In this paper, the multi-mode driving control is defined as the control strategy which switches a current driving control algorithm to the algorithm optimized in a recognized driving pattern. Based on the analysis of vehicle drive cycle, the driving pattern is defined according to the randomness of vehicle drive cycle. Four representative driving patterns are selected, which are composed of two urban driving patterns, two express way driving pattern. A total of 14 characteristic parameters are chosen to characterize the driving patterns. The multi-hierarchical comprehensive evaluation based on fuzzy comprehensive evaluation for vehicle drive conditions is introduced, which in driving decides periodically the representative driving pattern that is closest to a current drive cycle by comparing the correlation related to 14 characteristic parameters. The hierarchical system of vehicles driving patterns characteristic parameters is set up. Using an actual drive cycle as an example, the working condition is evaluated using the weighted average of fuzzy comprehensive evaluation model with comprehensive consideration of the influence of multiple factors. The analysis of vehicle drive cycle can be used to guide the design of HEVs powertrain and the multi-mode control algorithm using real-time online identification of drving pattern can be developed to optimize the performance of HEVs.

Keywords: Drive cycle; driving pattern; fuzzy evaluation; multi-mode control;

1. Introduction

The actual drive cycle of vehicles is random and uncertain which considerably affects the emissions and fuel efficiency of HEV, and especially the driving cycle and driving habits that have more sensitive influence on HEV than internal combustion engine vehicles. Currently, most of the hybrid power train parameters matching and control strategy optimization are obtained based on the analysis of a specific drive cycle. If the drive control strategy of HEV is not suitable for current drive cycle, it will have worse performance of fuel consumption and emissions than internal combustion engine vehicles (Song *et al,* 2016).

The hybrid buses have the characteristics of fixed driving route and strong cycle repeatability, which can realize the on-line identification and application of control strategy and typical working conditions. The selection of HEV powertrain structure, parameter matching, and test development must be based on the reasonable actual drive cycle. Additionally, the simulation analysis and performance verification of the whole vehicle should be conducted on the basis of the drive cycles (Luo *et al*, 2007).

The existing recognition methods of working condition mainly include neural network recognition method, fuzzy inference recognition method, etc(Montazeri-Gh M and Mahmoodi-k M,2015). It needs a lot of data training to identify the working condition accurately by using neural network. However, due to the complexity of the actual working condition and many emergencies, it is difficult to obtain a large number of accurate data samples for its learning. The driving pattern recognition based on fuzzy discrimination can contain all kinds of information. It can make the same kind of signals achieve different effects under different operations by changing the fuzzy rules, and has good following and filtering characteristics (Hao *et al,* 2016).

Yang (2014) established a classification and identification sample by dividing the standard working conditions, and established a working condition identifier based on the limit learning machine to complete the identification of the cycle working conditions. Lian(2016) proposed an adaptive control strategy based on fuzzy on-line identification for a parallel hybrid electric bus. The algorithm of fuzzy on-line identification is designed to identify the actual driving conditions of the vehicle. The corresponding optimal control parameters are called according to the results of condition identification. The experimental results showed that the designed fuzzy recognition method can complete the recognition of driving condition type. In order to overcome the lack of adaptability of PHEV powertrain control strategy in complex driving cycle, Chen(2017) proposed a route-based fuzzy adaptive control strategy of PHEV and the results showed that the method can improve the economic performance.

Vehicle have random actual working conditions and the characteristics of fuzzy information, which can be described and studied using fuzzy set. Due to the large amount of

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calculation, many kinds of parameters and wide range of features, fuzzy recognition algorithm is applied in this study. It can recognize by quantifying the membership characteristics of computational data and standard data, which can eliminate the interference of noise array and accurately reflect the belonging of recognition object. In addition, fuzzy recognition has the advantages of fast calculation speed and strong real-time performance, which is applicable to the identification of driving conditions in this study.

The drive cycles of vehicles are not only the characteristics manifested by vehicle itself, but also evaluators' understanding of vehicle performance from different purposes. It can be understood as the evaluation subjects' qualitative descriptions of objective phenomenon. In order to make the evaluation object of qualitative description distinguished and compared, some quantitative standards are needed.

2. Multi-mode Drive Control

Multi-mode drive control is defined as a kind of control strategy, and it can convert the present drive control algorithm into the optimized algorithm of representative driving pattern after identification (Lei *et al*, 2017). By contrast, single mode control is the control strategy that only has one drive control algorithm. The use of driving pattern recognition can make drive control strategy periodically adapted to current drive mode. To achieve this goal, simulation or experiment was conducted on the four typical driving patterns, and then the control parameters in the working index were optimized, thereby reducing fuel consumption and improving emission performance. These control parameters were stored in the vehicle control unit memory (Zhang & Xiong, 2015).

Control parameters are composed of weighting factors of working indexes, which are used to determine the indexes such as engine power. In actual driving, control parameters change to be the ones most suitable for current driving pattern according to the results of driving pattern recognition (Jeon *et al*, 2002).

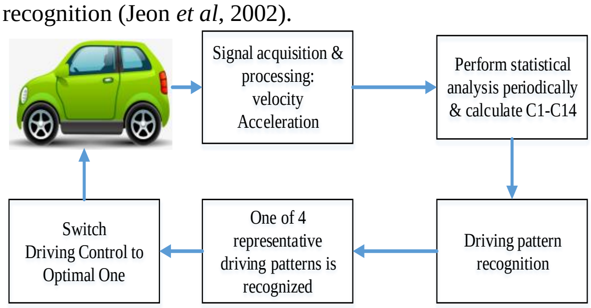

Figure 1. Multi-mode control principle diagram.

Fig.1 shows the multi-mode drive control diagram. First of all, each representative driving pattern control parameters were optimized so as to reduce fuel consumption and emissions. Such process could be finished through simulation. Thus, velocity and acceleration signals were stored in the vehicle control unit memory through the sensor measurement. The characteristic parameters were obtained through the statistical analysis of stored signals at short intervals. These results, as the input of fuzzy evaluation of vehicle drive cycles, recognized current driving pattern as one of four representative typical driving patterns. According to the result of driving pattern recognition, the drive control algorithm was turned into the optimized algorithm (Nicolas *et al*,2016).

3. Multi-hierarchical Comprehensive Evaluation Method Based on Fuzzy Comprehensive Evaluation

The basic idea of fuzzy comprehensive evaluation is to make reasonable comprehensive evaluation using fuzzy linear transformation principle and maximum degree of membership, and considering various factors related to the evaluated object (Liu *et al*, 2013).

It is assumed that there are *m* factors related to the evaluated object, and it is expressed with $U=\{u_1,u_2,\cdots,\ \mathrm{u}_m\}$ and named as the factor set. It represents *m* properties of the object. Besides, it is assumed that there are *n* possible comments, and it is expressed with $V=\{\mathrm{v}_1,v_2,\cdots,\ \mathrm{v}_n\}$ and named as the evaluation set.

For the significance of comprehensive evaluation, when the individual factor u_i is considered, the membership degree of u_i evaluation for the evaluation v_j is $r_{ij}\left(j=1,2,\cdots,n\right)$; for the result through the generalized fuzzy "and" operation $\left(a_{i}\hat{*}r_{ij}\right)$ expressed with r_{ij}^{*} ,when various factors are comprehensively considered, the membership degree of u_i evaluation for v_j means the adjustment on r_{ij} when the influence degree a_i of factor . u_i .on the total evaluation is considered. Finally, the adjusted membership degree is comprehensively processed through generalized fuzzy "or" operation so as to obtain reasonable comprehensive evaluation results.

When there are many elements in factor set *U*, the importance coefficient of each factor is correspondingly smaller, and it is often difficult to distinguish the superiority order of things in the system, and impossible to obtain meaningful evaluation results. For this kind of situation, the elements in factor set *U* can be divided into several categories according to certain properties; people can first make comprehensive evaluation on each kind of factors (fewer elements), and then conduct high-level comprehensive evaluation of the "class" element among the evaluation results (Shen *et al*, 2009). The specific method is as follows:

Assuming the importance degree subset of U_i is A_i , and the comprehensive evaluation matrix of k_i factors in U_i for V is R_i , the first level model $M\left(\hat{*},\check{*}\right)$ is selected for the fuzzy comprehensive evaluation on U_i . It is assumed that the fuzzy comprehensive evaluation set of U_i is as follows:

$$B_i=A_i*R_i=\left(b_{i1},b_{i2},\cdots,b_{in}\right)\qquad\left(i=1,2,\cdots,N\right)\tag{1}$$

Assuming importance degree fuzzy subset of $U=\{U_1,U_2,\cdots,\ \mathrm{U}_N\}$ factor is as follows:

$$A=\{A_1,A_2,\cdots,\ \mathrm{A}_N\}\tag{2}$$

Based on Equation (1), the second level comprehensive evaluation matrix is constructed:

$$R=\begin{pmatrix}B_1\\B_2\\\vdots\\B_N\end{pmatrix}=\begin{pmatrix}A_1*R_1\\A_2*R_2\\\vdots\\A_N*R_N\end{pmatrix}\tag{3}$$

Then, the second level fuzzy comprehensive evaluation for U is as follows:

$$B = A * R = (b_1, b_2, \cdots, b_n) \tag{4}$$

Finally, using the principle of maximum membership degree, the level (evaluation) corresponded by the maximum b_i is the best evaluation result.

4. The Classification of Vehicle Drive Mode

4.1. Vehicle Characteristic Parameters of Drive cycle

Vehicle driving pattern can be described with a variety of standard. This paper defines it with drive cycle working condition, and describes it with the recommended parameters in Table 1[5]. For vehicle driving cycle, the factor set was $U = [C1, C2, \cdots, C14]$. Because there are many factors and the weight need to meet $\sum \alpha_i = 1$, the weight of some factors would be smaller. Therefore, the factor set is further classified, and then factors within each level are comprehensively evaluated; finally, the high level of comprehensive evaluation is conducted on the evaluation results.

Table 1. Fourteen characteristic parameters of driving patterns.

Parameters	Meaning
C1	Average circling speed [km/h]
C2	Average operating speed after removing the parking time, V>0.5km/h[km/h]
C3	Parking time /total time [%]
C4	Accelerating kinetic energy under unit mass and distance (PKE) [m/s^2]
C5	Average acceleration [m/s^2], a>0.1 m/s^2
C6	Average deceleration [m/s^2], a<-0.1 m/s^2
C7	The number of parking per kilometer
C8	Average start-stop time (from starting and parking) [s]
C9	Acceleration time/total time [%]
C10	Deceleration time /total time [%]
C11	Acceleration standard deviation [m/s^2]
C12	Deceleration standard deviation [m/s^2]
C13	Maximum speed [km/h]
C14	Speed standard deviation [km/h]

In Table 1, C4 denotes the speed kinetic energy under unit mass and unit travel distance. The calculation formula is as follows:

$$PKE = \sum \frac{V_f^2 - V_i^2}{x}, \frac{dV}{dt} > 0 \tag{5}$$

In Equation (5), V_f and V_i respectively denote the start and final speed for each time of acceleration; x is the total travel distance.

C5 denotes the average acceleration of the whole acceleration process; C6 denotes the average deceleration of the whole deceleration process; C11 is acceleration standard deviation. For the selected driving pattern, the average acceleration of each driving pattern (C5) was firstly solved, the square root of the squares of the sum of each value and average deviation is the acceleration standard deviation. Similarly, C12 is the deceleration standard deviation; C14 is the corresponding average circling speed standard deviation, which can refer to the calculation of acceleration standard deviation.

Four representative driving patterns are selected, including two urban driving patterns and two highway drive patterns, shown in Fig. 2. And the dynamic performance of each driving pattern was sorted, which concretely describes the composition of each driving pattern and the statistics characteristics of the speed curve.

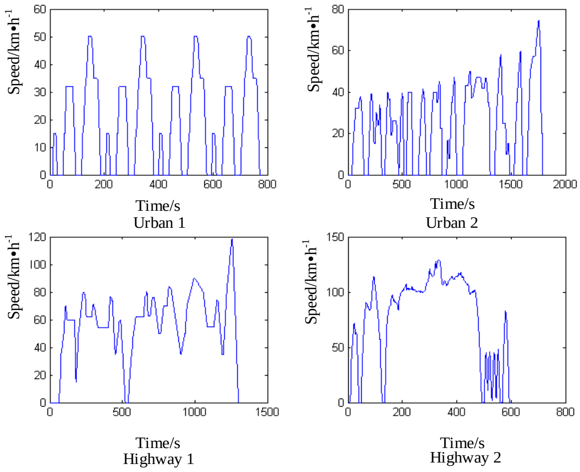

Figure 2. Four driving patterns.

The four specific driving patterns are described using the parameters specified in Table 1, and the specific values are shown in Table 2.

Table 2. Characteristic Parameter Values of Four Driving Patterns.

Characteristic Parameter	Urban 1	Urban 2	Highway 1	Highway 2
C1/km·h^{-1}	18.73	24.57	57.22	77.15
C2/km·h^{-1}	28.1	31.95	61.22	82.65
C3/%	30.8	23.12	6.96	6.66
C4/m·s^{-2}	0.2918	0.1612	0.2102	0.4573
C5/m·s^{-2}	0.13	0.1	0.1	0.28
C6/m·s^{-2}	-0.13	-0.1	-0.1	-0.29
C7	4	7.25	0.3	0.38
C8/s	45	120	607.5	109.4
C9/%	21.5	30.87	34.08	40.61
C10/%	18.5	28.2	32.62	40.27
C11/m·s^{-2}	0.1493	0.1493	0.1493	0.1493
C12/m·s^{-2}	-0.1578	-0.1578	-0.1578	-0.1578
C13/km·h^{-1}	50	74.52	118.43	129.2
C14/km·h^{-1}	47.84	47.84	47.84	47.84

4.2. The Classification of Factor Set and Determination of Weight

The fuzzy evaluation of vehicle drive cycles involves many factors, so the factors involved are divided into several categories in accordance with certain attributes, and then ordered from low to high level, as shown in Fig.3. Comprehensive evaluation is first conducted on the early levels of each kind, and then higher level of comprehensive evaluation is implemented on the class of evaluation results of each type so as to obtain the quantitative evaluation results that accorded with the actual situations.

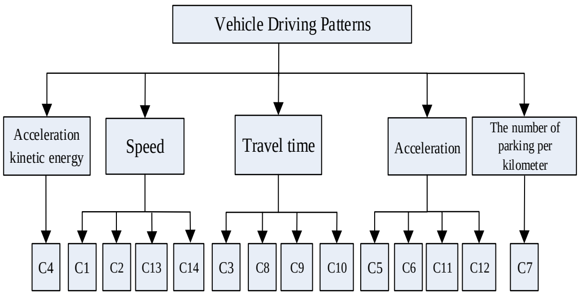

Figure 3. The hierarchical system of vehicles driving patterns Characteristic parameters.

For the weight of the characteristic parameters that described the vehicle driving pattern, the weight value shown in Table 3 are adopted.

Table 3. Characteristic Parameters and the Weight of Four Driving Patterns.

First level index and weight		Second level index and weight	
Speed	0.3	Average circling speed	0.33
		Average speed after removing the parking time	0.33
		Maximum speed	0.17
		Speed standard deviation	0.17
Travel time	0.25	Parking time/total time	0.4
		Average start-stop time (from starting to parking)	0.2
		Acceleration time/total time	0.2
		Deceleration time/total time	0.2
Acceleration	0.3	Average acceleration	0.33
		Average deceleration	0.33
		Acceleration standard deviation	0.17
		Deceleration standard deviation	0.17
Acceleration kinetic energy	0.1	accelerating kinetic energy under unit mass and unit distance	1
The number of parking per kilometer	0.05	The number of parking per kilometer	1

4.3. The Determination of Evaluation Set

Evaluation sets is a direct description and representation form of each level factors evaluation results. It is necessary to establish the corresponding evaluation set for each level of factors. It is determined the evaluation structure of various factors in the model are four grades, namely, 4 elements in V (m = 4) are expressed with V = {V1, V2, V3 and V4}.

The second level of factors are the base factors of comprehensive evaluation, namely, the direct survey evaluation factors. And the first level factor and the total target are the comprehensive reflection about the evaluation results of several factors. Evaluation sets represent the comprehensive evaluation results in the form of membership degree, and can fully reflect the evaluation.

For the fuzzy evaluation of vehicles working mode, four driving patterns are adopted as the evaluation result. Therefore, the key problem was how to determine the membership degree of elements in the factor sets. By taking Parameters C1 and C2 as examples, the membership function of driving pattern parameters is listed below.

(1) Average circling speed

Normal distribution is used as the membership function of average circling speed, and the average value is the average circling speed obtained by calculation. Besides, the variance is the average cycling speed standard deviation of four driving patterns. With urban drive cycle 1 as an example, the normal distribution value is listed in Equation (6):

$$\mu(C1) = e^{-\left(\frac{x-18.73}{47.84}\right)^2} \tag{6}$$

The membership degree curve of average circling speed under the four driving patterns is shown in Fig. 4.

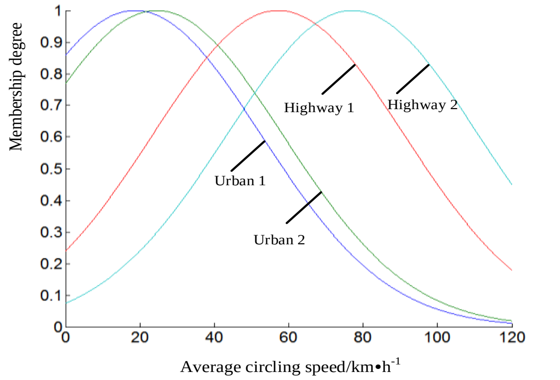

Figure 4. Membership Curve of Vehicles Average Circling Speed.

(2) Average speed after removing the parking time

Being similar to C1, with urban driving pattern 1 as an example, the normal distribution was taken, and the average is the average running speed after removing parking time, the variance is the average speed standard deviation of the four driving pattern2. The membership of average speed after removing the parking time is shown in Equation (7).

$$\mu(C2) = e^{-\left(\frac{x-28.1}{44.65}\right)^2} \tag{7}$$

The membership curve of average speed after removing the parking time under the four driving pattern is shown in Fig.5.

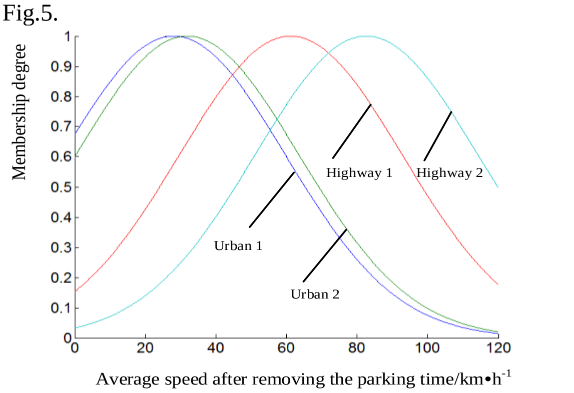

Figure 5. Membership curve of vehicle average speed after removing the parking time

Similarly, the characteristic parameters membership functions under the four driving pattern could be obtained, as shown in Table 4.

Table 4. Membership functions of characteristic parameters under four driving patterns.

	Urban 1	Urban 2	Highway 1	Highway 2
C1	$e^{-\left(\frac{x-18.75}{47.84}\right)^2}$	$e^{-\left(\frac{x-24.57}{47.84}\right)^2}$	$e^{-\left(\frac{x-57.22}{47.84}\right)^2}$	$e^{-\left(\frac{x-77.15}{47.84}\right)^2}$
C2	$e^{-\left(\frac{x-28.1}{44.65}\right)^2}$	$e^{-\left(\frac{x-31.95}{44.65}\right)^2}$	$e^{-\left(\frac{x-61.22}{44.65}\right)^2}$	$e^{-\left(\frac{x-82.65}{44.65}\right)^2}$
C3	$e^{-\left(\frac{x-0.308}{0.2087}\right)^2}$	$e^{-\left(\frac{x-0.2312}{0.2087}\right)^2}$	$e^{-\left(\frac{x-0.0696}{0.2087}\right)^2}$	$e^{-\left(\frac{x-0.0666}{0.2087}\right)^2}$
C4	$e^{-\left(\frac{x-0.2918}{0.2249}\right)^2}$	$e^{-\left(\frac{x-0.1612}{0.2249}\right)^2}$	$e^{-\left(\frac{x-0.2102}{0.2249}\right)^2}$	$e^{-\left(\frac{x-0.4573}{0.2249}\right)^2}$
C5	$e^{-\left(\frac{x-0.13}{0.1493}\right)^2}$	$e^{-\left(\frac{x-0.1}{0.1493}\right)^2}$	$e^{-\left(\frac{x-0.1}{0.1493}\right)^2}$	$e^{-\left(\frac{x-0.1}{0.1493}\right)^2}$
C6	$e^{-\left(\frac{x+0.13}{0.1578}\right)^2}$	$e^{-\left(\frac{x+0.1}{0.1578}\right)^2}$	$e^{-\left(\frac{x+0.1}{0.1578}\right)^2}$	$e^{-\left(\frac{x+0.29}{0.1578}\right)^2}$
C7	$e^{-\left(\frac{x-4}{5.7633}\right)^2}$	$e^{-\left(\frac{x-7.25}{5.7633}\right)^2}$	$e^{-\left(\frac{x-0.3}{5.7633}\right)^2}$	$e^{-\left(\frac{x-0.38}{5.7633}\right)^2}$
C8	$e^{-\left(\frac{x-45}{450.2385}\right)^2}$	$e^{-\left(\frac{x-120}{450.2385}\right)^2}$	$e^{-\left(\frac{x-607.5}{450.2385}\right)^2}$	$e^{-\left(\frac{x-109.4}{450.2385}\right)^2}$
C9	$e^{-\left(\frac{x-0.215}{0.1378}\right)^2}$	$e^{-\left(\frac{x-0.3087}{0.1378}\right)^2}$	$e^{-\left(\frac{x-0.3408}{0.1378}\right)^2}$	$e^{-\left(\frac{x-0.4061}{0.1378}\right)^2}$
C10	$e^{-\left(\frac{x-0.185}{0.1574}\right)^2}$	$e^{-\left(\frac{x-0.282}{0.1574}\right)^2}$	$e^{-\left(\frac{x-0.3262}{0.1574}\right)^2}$	$e^{-\left(\frac{x-0.4027}{0.1574}\right)^2}$
C11	$e^{-(x-0.1493)^2}$	$e^{-(x-0.1493)^2}$	$e^{-(x-0.1493)^2}$	$e^{-(x-0.1493)^2}$
C12	$e^{-(x+0.1578)^2}$	$e^{-(x+0.1578)^2}$	$e^{-(x+0.1578)^2}$	$e^{-(x+0.1578)^2}$
C13	$e^{-\left(\frac{x-50}{64.396}\right)^2}$	$e^{-\left(\frac{x-74.5}{64.396}\right)^2}$	$e^{-\left(\frac{x-118.4}{64.396}\right)^2}$	$e^{-\left(\frac{x-129.2}{64.396}\right)^2}$
C14	$e^{-(x-47.84)^2}$	$e^{-(x-47.84)^2}$	$e^{-(x-47.84)^2}$	$e^{-(x-47.84)^2}$

5. Case Study

By taking one actual drive cycle as the example, the fuzzy evaluation is conducted and the speed curve is shown in Fig. 6.

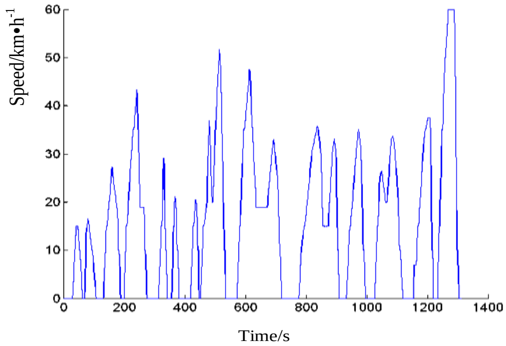

Figure 6. Speed curve of the vehicle drive cycle to be Evaluated

The characteristic parameters of the working condition are as follows:

$$U=\{16.1,19.83,30.37,0.285,0.11,-0.11,2.5,67.64,0.3485,0.2336,0.1539,-0.1643,60,54.135\}$$

After bringing the value to Table 4, the membership of the factors in different driving patterns could be obtained. Multi-hierarchical fuzzy evaluation is conducted according to the classification method shown in Table 3. In accordance with the classification shown in Table 3, second level indexes are comprehensively evaluated in the first place. The evaluation matrix of the second layer was established.

By definition, the second level indexes evaluation matrix are respectively as follows:

$$R_1=\begin{bmatrix}0.99 & 0.97 & 0.48 & 0.2\\ 0.97 & 0.93 & 0.42 & 0.13\\ 0.98 & 0.95 & 0.44 & 0.32\\ 0 & 0 & 0 & 0\end{bmatrix}$$

$$R_2=\begin{bmatrix}0.99 & 0.87 & 0.28 & 0.27\\ 0.99 & 0.98 & 0.24 & 0.99\\ 0.39 & 0.92 & 0.99 & 0.84\\ 0.90 & 0.91 & 0.71 & 0.32\end{bmatrix}$$

$$R_3=\begin{bmatrix}0.98 & 1 & 1 & 0.27\\ 0.98 & 1 & 1 & 0.27\\ 1 & 1 & 1 & 1\\ 1 & 1 & 1 & 1\end{bmatrix}$$

The weight matrix are as follows:

$$A_1=\begin{bmatrix}0.33 & 0.33 & 0.17 & 0.17\end{bmatrix}$$

$$A_2=\begin{bmatrix}0.4 & 0.2 & 0.2 & 0.2\end{bmatrix}$$

$$A_3=\begin{bmatrix}0.33 & 0.33 & 0.17 & 0.17\end{bmatrix}$$

By using fuzzy transformation and the first model, namely:

$$b_j=\overset{m}{\underset{i=1}{\vee}}\left(a_i\wedge r_{ij}\right)\qquad\left(j=1,2,\cdots,n\right)$$

The corresponding results could be obtained:

$$B_1=A_1\circ R_1=\begin{bmatrix}0.33 & 0.33 & 0.33 & 0.2\end{bmatrix}$$

$$B_2=A_2\circ R_2=\begin{bmatrix}0.4 & 0.4 & 0.28 & 0.27\end{bmatrix}$$

$$B_3=A_3\circ R_3=\begin{bmatrix}0.33 & 0.33 & 0.33 & 0.27\end{bmatrix}$$

After combining the evaluation results of the second level indexes with the membership functions of two independent index, the evaluation matrix of the first level indexes are obtained as follows:

$$R=\begin{bmatrix} 0.33 & 0.33 & 0.17 & 0.17 \\ 0.4 & 0.2 & 0.2 & 0.2 \\ 0.33 & 0.33 & 0.17 & 0.17 \\ 1 & 0.74 & 0.9 & 1 \\ 0.94 & 0.51 & 0.86 & 0.87 \end{bmatrix}$$

The weights allocation of the first level indexes is as follows:

$$A=\begin{bmatrix} 0.3 & 0.25 & 0.3 & 0.1 & 0.05 \end{bmatrix}$$

After conducting fuzzy transformation, the corresponding results could be found:

$$B=A\circ R=\begin{bmatrix} 0.3 & 0.3 & 0.2 & 0.2 \end{bmatrix}$$

The fuzzy evaluation results obtained through the first model have the same membership degree for the urban driving pattern 1 and 2. Because the main element decided type fuzzy comprehensive evaluation model considers only the main influencing factors, and ignores the influence of other factors, it is more suitable for the situation that the single evaluation optimization could be the optimal comprehensive evaluation.

In order to comprehensively consider the effect of multiple factors, the weighted average fuzzy comprehensive evaluation model is adopted.

$$b_j=\sum_{i=1}^{m}\left(a_i\cdot r_{ij}\right) \qquad \left(j=1,2,\cdots,n\right)$$

The second level indexes are evaluated, and the following results are obtained:

$$B_1=A_1\circ R_1=\begin{bmatrix} 0.8143 & 0.7885 & 0.3718 & 0.1633 \end{bmatrix}$$

$$B_2=A_2\circ R_2=\begin{bmatrix} 0.852 & 0.91 & 0.5 & 0.538 \end{bmatrix}$$

$$B_3=A_3\circ R_3=\begin{bmatrix} 0.9868 & 1 & 1 & 0.5182 \end{bmatrix}$$

The evaluation matrix of the first level indexes are as follows:

$$R=\begin{bmatrix} 0.8143 & 0.7885 & 0.3718 & 0.1633 \\ 0.8520 & 0.91 & 0.5 & 0.538 \\ 0.9868 & 1 & 1 & 0.5182 \\ 1 & 0.74 & 0.9 & 1 \\ 0.94 & 0.51 & 0.86 & 0.87 \end{bmatrix}$$

The weights allocation of the first level indexes is as follows:

$$A=\begin{bmatrix} 0.3 & 0.25 & 0.3 & 0.1 & 0.05 \end{bmatrix}$$

After conducting fuzzy transformation, we could find

$$B=A\circ R=\begin{bmatrix} 0.9 & 0.86 & 0.67 & 0.48 \end{bmatrix}$$

Visibly, the selected actual drive cycle is closer to the selected urban driving pattern 1.

Seen from the results above, the fuzzy comprehensive evaluation method can be effectively used to distinguish the working conditions of vehicles. The characteristic parameters of the selected driving mode meet the needs of the actual working conditions and the characteristics of the randomness of the actual working conditions. On this basis, combining with other information such as driver's intention, the energy management strategy based on condition adaptation can meet the real-time control and optimization of vehicle management strategy under various conditions. The results can be used not only in hybrid vehicles, but also in electric vehicles and fuel cell vehicles.

6. Conclusions

Due to the fuzzy characteristics of vehicle driving data, this paper proposes a method of vehicle driving pattern recognition based on fuzzy discrimination.

Firstly, the principle of multi-mode drive control is introduced. Besides, the multi-level comprehensive evaluation based on fuzzy comprehensive evaluation for vehicle drive cycle is introduced. The results of comprehensive evaluation are judged according to the maximum membership principle; The vehicle driving pattern is defined with the drive cycling working condition.

Four typical driving patterns are selected to define the typical driving pattern of HEV, including two urban drive cycles and two highway drive cycles. The driving patterns are described using 14 representative characteristic parameters (C1 - C14), which are closely related to the speed, acceleration, and so on. According to the composition of drive cycles and the statistical characteristics for each speed curve, the characteristic parameters of four driving patterns are defined; The factors relating to four riving patterns are divided into five categories according to property, and the weights of their characteristic parameters are selected. The evaluation sets of evaluation results of factors at various levels are established. The membership functions of driving pattern parameters are determined; With a certain actual drive cycle as an example, the working condition is evaluated using the weighted average of fuzzy comprehensive evaluation model with comprehensive consideration of the influence of multiple factors.

Based on the analysis of the historical driving data, the energy management strategy based on multi-hierarchical fuzzy comprehensive can judge the driving condition type of the current and future vehicles in a short time, and dynamically adjusts the control strategy according to the condition type to achieve the adaptive energy management strategy.

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