Fuzzy Adaptive Control Strategy with Improved PSO Algorithm for Parallel Hybrid Electric Vehicle

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Abstract* — In order to further improve the whole vehicle economy of a novel plug-in hybrid electric vehicle (PHEV), considering two main factors, which are the driving working conditions and the driving distance, influencing the whole vehicle economy, a control strategy based on fuzzy self-adaptive online recognition is provided. A fuzzy working condition recognition algorithm is designed to online recognize the working condition types of actual driving of the vehicle. According to a minimum equivalent fuel consumption control algorithm and a battery electric quantity balance control method, corresponding optimal control parameters are called combining with a working condition recognition result, and real-time optimizing calculation is carried out on power distribution on an engine and a battery to control the whole vehicle. Finally, simulation analysis is carried out on an energy management control strategy of the whole vehicle. The result shows that under the new European driving cycle (NEDC) working condition at an equal driving distance, compared with a fixed parameter energy management strategy, the fuzzy self-adaptive online recognition energy management strategy can lower the whole vehicle equivalent fuel consumption per hundred kilometers by above 5%, and thus the whole vehicle economy of the PHEV is improved.

Keywords - Parallel hybrid vehicle; Mode transition; Transient response; Fuzzy adaptive control; Experimental validation

I. INTRODUCTION

That the hybrid electric vehicle reasonably distributes the energy among all system parts in the premise of meeting the power performance indexes of the whole vehicle so as to acquire the optimal energy management strategy depended by the optimal performance is a focus and hotspot of research in recent years[1]. Factors, including the driving distance and the driving working condition of the vehicle, can directly influence distribution of power sources and partition of working modes of the PHEV, and thus influencing the whole vehicle economy of the PHEV. Chen uses a matrix partition (DIRECT) global optimization algorithm to carry out optimized analysis on values of main control parameters of the PHEV energy management strategy, and a conclusion that the key factors, influencing the whole vehicle economy of the PHEV, include the driving working condition and the driving distance of the vehicle is obtained[2]. Stephen carries out global optimization analysis on the energy management strategy of the PHEV under different cycle working condition by adopting the Bellman principle and a particle swarm optimization (PSO) algorithm to obtain a conclusion that formulation of the PHEV energy management strategy must consider the influence of the driving working condition and the driving distance of the vehicle, but all of them do not propose a concrete solution[3]. Zhang establishes a road model for vehicle driving by adopting a neural network algorithm according to GPS, GIS, history and real-time traffic data and apply to the PHEV energy management strategy, but the method needs a great quantity of traffic data and is unuseful at the present stage[4]. The neural network algorithm is adopted to carry out vehicle driving working condition recognition and is applied to the energy management strategy of the hybrid electric vehicle (HEV), but the influence of the driving distance of the vehicle is not considered[5-10].

Aiming at the above problems, in this paper, the new European driving cycle working conditions for example, the real-time optimization control strategy based on fuzzy self-adaptive online recognition is provided. Firstly, the typical working conditions, according with the local actual driving road characteristics, is constructed based on a hybrid electric vehicle data collecting and monitoring system which is independently developed by a research group; and secondly, the fuzzy recognition algorithm is designed to recognize the actual working condition of the vehicle online, a working condition self-adaptive control strategy is formulated combining with the minimum equivalent fuel consumption control algorithm and the battery electric quantity balance control method, the powers of the engine and the motor are optimally distributed in real time, and the advantage of the self-adaptive control strategy can be fully exerted when the adaptation of a hybrid electric bus is improved and the online real-time calculation amount[11,12].

II. PROBLEM FORMULATION

In this paper, the control strategy based on driving working condition recognition is that typical cycle working conditions with a certain amount are selected, possible driving working condition types of a vehicle are covered, and off-line optimization is carried out on an energy management strategy of the typical cycle working conditions; and when the vehicle actually runs, the typical cycle working condition, similar to the current driving working condition, is obtained through working condition recognition, and the control strategy is regulated online.

When the vehicle starts, data of the driving working conditions of the vehicle begins to be collected; once a sampling time reaches a certain recognition period (the recognition period is selected to be 200s according to a relationship between the recognition period and the recognition accuracy in a document [13]), characteristic parameters of the driving working condition of the vehicle are extracted, and then contrastive analysis is carried out on the characteristic parameters and characteristic parameters of the typical cycle working conditions through fuzzy pattern recognition to determine the type of the driving working condition of the vehicle.

A. Selection of typical cycle working condition and characteristic parameter

Selection of the typical cycle working condition is crucial to recognition of the driving working condition of the vehicle. In this paper, the selected representative cycle working conditions are a New York City cycle (NYCC) working condition, a UDDS cycle working condition, an NEDC cycle working condition and an HWFET cycle working condition.

According to the influences of the characteristic parameters on the whole vehicle economy, this paper selects the following five characteristic parameters which are cyclic average vehicle speed u_{m} (an average speed of the vehicle in the whole driving cycle), an average running vehicle speed u_{mr} (an average speed of the vehicle except the parking time), a parking time ratio η, an average acceleration α_{acc} and an average deceleration α_{dec}.

In this paper, the selected characteristic parameters of the typical cycle working conditions are shown as Equation (8). Seen from the Equation (8), the characteristic parameters have the gradation performance and can well reflect the actual running working condition of the vehicle.

B. Extraction of characteristic parameters of driving working condition

After the vehicle starts, the characteristic parameters of the driving working condition of the vehicle can be extracted according to the real-time vehicle speed and the corresponding time node data, and calculation formulas are respectively shown as follows:

$$u_{\mathrm{m}} = \int u\mathrm{d}t / t,\ u_{\mathrm{mr}} = \int u\mathrm{d}t / \int t'\mathrm{d}t \tag{1}$$

$$\eta = (t - \int t'\mathrm{d}t) / t \times 100\% \tag{2}$$

$$\alpha_{\mathrm{acc}} = \int \frac{\mathrm{d}u}{3.6\mathrm{d}t_{\mathrm{acc}}}\mathrm{d}t / \int t_{\mathrm{acc}}\mathrm{d}t \tag{3}$$

$$\alpha_{\mathrm{dec}} = \int \frac{\mathrm{d}u}{3.6\mathrm{d}t_{\mathrm{dec}}}\mathrm{d}t / \int t_{\mathrm{dec}}\mathrm{d}t \tag{4}$$

in the formulas, u is the real-time vehicle speed; t is the running time of the vehicle; t' is the running time of the vehicle when the vehicle speed is not 0; t_{acc} is the accelerated running time of the vehicle; and t_{dec} is the decelerated running time of the vehicle.

C. Fuzzy pattern recognition of driving working conditions

Based on a system optimization fuzzy set theory[14], driving working condition recognition is carried out by adopting a fuzzy recognition algorithm.

The 5 characteristic parameters after extraction of the characteristic parameters of the driving working conditions form a sample matrix to be recognized, so that a ample has 5 indexes, and the index vector is $[v_{\mathrm{m}}\quad v_{\mathrm{mr}}\quad \eta\quad a_{\mathrm{a}}\quad a_{\mathrm{d}}]^{\mathrm{T}}$. As the matrix needs to carry out normalization processing, only one group in the matrix cannot realize normalization processing, and 4 groups of parameters of the standard working conditions are added, but only the first group is recognized during recognition. An index characteristic value matrix of the matrix to be recognized is expressed as follows:

$$\bar{\boldsymbol{Y}} = (\bar{u}_{\mathrm{m}}, \bar{u}_{\mathrm{mr}}, \bar{\eta}, \bar{\alpha}_{\mathrm{acc}}, \bar{\alpha}_{\mathrm{dec}}) \tag{5}$$

In the formula: x_{ij} is a characteristic value of j indexing i, and i=1,2,⋯,5.

As the characteristic values of five indexes have differences in dimension grade, and normalization processing needs to be carried out.

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$$\begin{cases} r_{ij} = \dfrac{x_{ij} - x_{i\min}}{x_{i\max} - x_{i\min}}, \\ r_{ij} = \dfrac{x_{i\max} - x_{ij}}{x_{i\max} - x_{i\min}}, \end{cases} \tag{6}$$

In the formula, $x_{i\max}$ and $x_{i\min}$ are the maximum characteristic value and the minimum characteristic value of the ith index; and r_{ij} is a normalized value of r_{ij} with the range to be larger than or equal to 0 and smaller than or equal to 1.

According to the formula (3), a relative membership degree matrix is calculated by substituting the formula (2)

$$\begin{bmatrix} r_{11} & r_{12} & \cdots & r_{15} \\ r_{21} & r_{22} & \cdots & r_{25} \\ \cdots & \cdots & \cdots & \cdots \\ r_{51} & r_{52} & \cdots & r_{55} \end{bmatrix} = (r_{ij})_{5\times5} \tag{7}$$

With f index characteristic values in 4 types as a such clustering center, the index characteristic values in 4 types can be expressed by using the fuzzy clustering center matrix.

$$\begin{bmatrix} s_{11} & s_{12} & \cdots & s_{1c} \\ s_{21} & s_{22} & \cdots & s_{2c} \\ \cdots & \cdots & \cdots & \cdots \\ s_{m1} & s_{m2} & \cdots & s_{mc} \end{bmatrix} = \begin{bmatrix} 1.000\,0 & 0.736\,5 & 0.205\,7 & 0.000\,0 \\ 0.747\,8 & 1.000\,0 & 0.377\,8 & 0.000\,0 \\ 0.000\,0 & 0.579\,3 & 0.983\,9 & 1.000\,0 \\ 0.000\,0 & 1.000\,0 & 0.984\,4 & 0.625\,0 \\ 0.250\,0 & 0.770\,8 & 1.000\,0 & 0.000\,0 \end{bmatrix} = [s_{ih}]_{5\times4} \tag{8}$$

In the formula: S_{ih} is a normalized number of the characteristic value of the index i in type h and is larger than or equal to 0 and smaller than or equal to 1.

According to the maximum subordination principle of fuzzy pattern recognition, the larger the Euclid approach degree value is, the closer the two kinds of driving working conditions is, so that the driving working condition belongs to which kind of typical cycle working condition can be determined by utilizing an Euclid approach degree formula, and then the control strategy of the corresponding typical cycle working condition is adopted.

III. CONTROLLER DESIGN

An SLAM algorithm[15,16] based on EKF mainly comprises two steps: a prediction process and an observation updating process. A system model is established firstly, and space environment is expressed by utilizing a combined state vector containing a k moment vehicle characteristic $x_v(k)$ and a road condition characteristic $x_m(k)$, namely,

$$x(k) = [x_v(k), x_m(k)]^T \tag{9}$$

A corresponding state covariance matrix is as follows:

$$P = \begin{bmatrix} P_v & P_{vm} \\ P_{vm}^{\mathrm{T}} & P_m \end{bmatrix} \tag{10}$$

wherein, P_{vm} expresses the correlation degree of the vehicle state vector and the road condition characteristic vector.

The prediction process: defining $u(k)$, serving as an arbitrary k moment control signal and $z(k)$, $Q(k)$ and $R(k)$, serving as observation values of a sensor, as corresponding covariance matrixes respectively. A prediction equation is as follows:

$$x(k+1/k) = F(k)x(k\,|\,k) + u(k) \tag{11}$$

$$z(k+1\,|\,k) = H(k)x(k+1\,|\,k) \tag{12}$$

$$P(k+1\,|\,k) = F(k)P(k\,|\,k)F^T(k) + Q(k) \tag{13}$$

wherein, $F(k)$ and $H(k)$ are a state transition matrix and an observation matrix of a k moment system respectively.

A fuzzy algorithm is to regulate a value of the covariance matrix R of observation noise online. The nature of the algorithm is to regulate the size of the covariance matrix R of observation noise by utilizing a fuzzy system according to the difference of an innovation actual covariance matrix and a theory covariance matrix. An equation of the innovation actual covariance matrix $C_{\ln nk}$ is as follows:

$$C_{\ln nk} = v(k)v^{\mathrm{T}}(k) \tag{14}$$

Our objective is to enable the difference value between the actual covariance matrix $C_{\ln nk}$ and the theory covariance matrix $S(k)$ to be minimum, namely enable $\Delta C_{\ln nk}$ to be minimum:

$$\Delta C_{\ln nk} = C_{\ln nk} - S(k) \tag{15}$$

The single-input and single-output fuzzy system is used in here. Input of the system is a diagonal element $\Delta C_{\ln nk}(j,j)$ of $\Delta C_{\ln nk}$, and output is a diagonal element variable $\Delta R(j,j)$ of the observation noise covariance matrix R. Input of the fuzzy system adopts three membership functions which are a negative value (N), a zero value (Z) and a positive value (P). Three fuzzy rules are as follows:

IF $\Delta C_{\ln nk}(j,j)$ is N THEN $\Delta R(j,j) = w_1$,

IF $\Delta C_{\ln nk}(j,j)$ is N THEN $\Delta R(j,j) = w_2$,

IF $\Delta C_{\ln nk}(j,j)$ is N THEN $\Delta R(j,j) = w_3$,

The three fuzzy rules adopt Guassian type and are guass1 (a_1,b_1), guass2 (a_2,b_2) and guass3 (a_3,b_3) respectively. Therefore, values, needing to be determined, in the fuzzy system are $a_1, a_2, a_3, b_1, b_2, b_3, w_1, w_2, w_3$.

IV. SIMULATION RESULTS

Long distance working condition is chosen for the optimization of fuzzy control management strategy, since PHEV has the highest requirement for energy management strategies. Thus, 15 of CYC_US06_HWY are selected as optimization working condition.

Let $w = 0.729\ 8$, $c_1 = c_2 = 1.496\ 2$, $T = 1\ 000$, $r(i,d) = 0.5 + (0.005)rand$, $N = 20$, $C_{id}(t) = 0.999$, $M_i = 0.5$ and the original value of the particle is $\psi_d \times M_i \times (2rand() - 1)$. Non-interface ADVISOR2002 is operated at Matlab command window.

The data in Table 1 derives from the imitation of original fuzzy control strategy and the one after modification. It can be drawn from Table 1 that after modification the oil consumption has decreased 0.31L every one hundred kilometer (saving 5.14% oil) and CO emission also has a reduction of 0.084g/km (decreasing 9.84%). NO_x and HC exhaust lower slightly as well. The reason can be expressed in Figure 1 that the engine operates where is more concentrated in optimization range. Therefore, the battery charging curve almost keeps the same shape during the global optimization, which indicates that fuzzy energy management strategy can help avoid the forced-discharge effectively.

TABLE 1. THE OPTIMIZED RUNNING EFFECT

	Oil consumption L/100 km	power-consumption kW • h	CO emission g/km	NO_x emission g/km	HC emission g/km
before optimization	6.03	4	0.853	0.204	0.125
after optimization	5.72	4	0.769	0.181	0.119

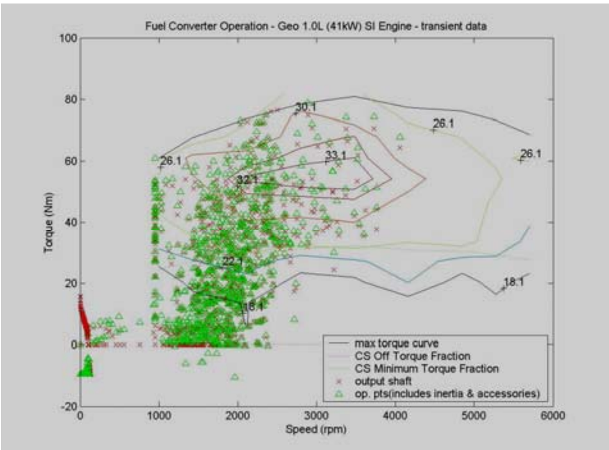

Figure 1.The engine operating point.

V. CONCLUSION

Aiming at the energy management strategy of some novel PHEV based on the rules, the control strategy based on fuzzy self-adaptation is provided, and a fuzzy recognition method is designed to online recognize the running working condition of the vehicle; and the optimal control parameter, corresponding to the current driving working condition of the vehicle, is called and updated in real time to be used for optimizing calculation in real time, and thus control parameters of the engine and the motor are obtained. It could be known by applying MATLAB/Simulink to carry out simulation contrastive analysis that relative to the fixed parameter energy management strategy, the fuzzy self-adaptive energy management strategy can effectively reduce the whole vehicle equivalent fuel consumption per hundred kilometers by above 5%, and thus the feasibility and the superiority of the fuzzy self-adaptive energy management strategy are verified.

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REFERENCES

[1] H. Borhan, A. Vahidi, A. M. Phillips, M. L. Kuang, I. V. Kolmanovsky, and S. Di Cairano, “MPC-based energy management of a power-split hybrid electric vehicle,” IEEE Transactions on Control Systems Technology, vol. 20, no. 3, pp. 593-603, 2012.

[2] L. Chen, F. Zhu, M. Zhang, Y. Huo, C. Yin, and H. Peng, “Design and analysis of an electrical variable transmission for a series-parallel hybrid electric vehicle,” IEEE Transactions on Vehicular Technology, vol. 60, no. 5, pp. 2354-2363, 2011.

[3] C. H. Stephan and J. Sullivan, “Environmental and Energy Implications of Plug-in Hybrid-electric Vehicles,” Environmental Science and Technology, vol. 42, no. 4, pp. 1185-1190, 2008.

[4] C. Zhang, A. Vahidi, P. Pisu, X. Li, and K. Tennant, “Role of terrain preview in energy management of hybrid electric vehicles,” IEEE Transactions on Vehicular Technology, vol. 59, no. 3, pp. 1139-1147, 2010.

[5] S. Adhikari, S. K. Halgamuge, and H. C. Watson, “An online power-balancing strategy for a parallel hybrid electric vehicle assisted by an integrated starter generator,” IEEE Transactions on Vehicular Technology, vol. 59, no. 6, pp. 2689-2699, 2010.

[6] H.-U. Rehman, “An integrated starter-alternator and low-cost high-performance drive for vehicular applications,” IEEE Transactions on Vehicular Technology, vol. 57, no. 3, pp. 1454-1465, 2008.

[7] J. T. B. A. Kessels, M. W. T. Koot, P. P. J. van den Bosch, and D. B. Kok, “Online energy management for hybrid electric vehicles,” IEEE Transactions on Vehicular Technology, vol. 57, no. 6, pp. 3428-3440, 2008.

[8] O. Reyss, G. Duc, P. Pognant-Gros, and G. Sandou, “Multivariable torque tracking control for E-IVT hybrid powertrain,” International Journal of Systems Science, vol. 40, no. 11, pp. 1181-1195, 2009.

[9] H. R. Liu and J. Yang, "Sliding-Mode Synchronization Control for Uncertain Fractional-Order Chaotic Systems with Time Delay," Entropy, vol. 17, no. 6, pp. 4202-4214, 2015.

[10] B. Zhang and S. Xu, “Delay-dependent Robust H∞ control for uncertain discrete-time fuzzy systems with time-varying delays,” IEEE Transactions on Fuzzy Systems, vol. 17, no. 4, pp. 809-823, 2009.

[11] M. Montazeri-Gh and M. Asadi, “Intelligent approach for parallel HEV control strategy based on driving cycles,” International Journal of Systems Science, vol. 42, no. 2, pp. 287-302, 2011.

[12] L. Wu, Y. Wang, X. Yuan, and Z. Chen, “Multiobjective optimization of HEV fuel economy and emissions using the self-

adaptive differential evolution algorithm," IEEE Transactions on Vehicular Technology, vol. 60, no. 6, pp. 2458-2470, 2011.

[13] A. L. Shen, W. H. Yuan, Q. S. Zuo, et al., "Intelligent optimization for logic threshold control parameter on parallel hybrid electric vehicle," Zhongnan Daxue Xuebao, vol. 43, no. 11, pp. 4306-4312, 2012.

[14] H. R. Liu, F. Y. Yi, and H. L. Yang, "Adaptive Grouping Cloud Model Shuffled Frog Leaping Algorithm for Solving Continuous Optimization Problems," Computational Intelligence and Neuroscience, vol. 2016, Article ID 5675349, 8 pages, 2016.

[15] J. Kim, T. Kim, B. Min, S. Hwang, and H. Kim, "Mode control strategy for a two-mode hybrid electric vehicle using electrically variable transmission (EVT) and fixed-gear mode," IEEE Transactions on Vehicular Technology, vol. 60, no. 3, pp. 793-803, 2011.

[16] F. Yan, J. Wang, and K. Huang, "Hybrid electric vehicle model predictive control torque-split strategy incorporating engine transient characteristics," IEEE Transactions on Vehicular Technology, vol. 61, no. 6, pp. 2458-2467, 2012.