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FUZZY ENERGY MANAGEMENT STRATEGY FOR A HYBRID ELECTRIC VEHICLE BASED ON DRIVING CYCLE RECOGNITION

J. WU[1,3)*], C.-H. ZHANG[2)] and N.-X. CUI[2)]

[1)]School of Mechanical Engineering, Shandong University, Jinan 250061, China
[2)]School of Control Science and Engineering, Shandong University, Jinan 250061, China
[3)]Department of Information Science and Technology, Shandong University of Political Science and Law, Jinan 250014, China

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ABSTRACT−By considering the effect of the driving cycle on the energy management strategy (EMS), a fuzzy EMS based on driving cycle recognition is proposed to improve the fuel economy of a parallel hybrid electric vehicle. The EMS is composed of driving cycle recognition and a fuzzy torque distribution controller. The current driving cycle is recognized by learning vector quantization in driving cycle recognition. The torque of the engine and the motor is controlled by a fuzzy torque distribution controller based on the required torque of the hybrid powertrain and the battery state of charge. The membership functions and rules of the fuzzy torque distribution controller are optimized simultaneously by using particle swarm optimization. Based on the identification results of driving cycle recognition, the fuzzy torque distribution controller selects the corresponding membership function and rule to control the hybrid powertrain. The simulation research based on ADVISOR demonstrates that this EMS improves fuel economy more effectively than fuzzy EMS without driving cycle recognition.

KEY WORDS : Energy management strategy, Hybrid electric vehicle, Fuzzy control, Driving cycle recognition

1. INTRODUCTION

The performance of a hybrid electric vehicle (HEV), which is a new type of multi-energy source vehicle, is closely related to the energy management strategy (EMS) adopted (Antoni, 2001). According to the characteristics of the vehicle powertrain and the real-time situation of the road, the EMS should distribute the drive power between the engine and the motor reasonably to realize efficient energy savings and low exhaust emissions without sacrificing HEV performance.

Based on the traditional system configuration and composition, a hybrid electric vehicle can be classified into the series, parallel or mix three categories. The parallel hybrid electric vehicle (PHEV) adopts two independent drive systems for the engine and the motor to reduce the deadweight and the manufacturing cost of vehicles, and thus the PHEV is a very promising structure. However, the EMS of PHEV is immature for the complex driving mode of PHEV. The logic threshold control strategy commonly used at present sets the initial value of the parameters by mostly depending on engineering experience and then adjusts these parameters by combining the "trial-and-error method". Although these strategies can offer a significant improvement in energy efficiency and are adopted widely in commercial HEV, it is clear that they do not guarantee an optimal result in all situations or allow the vehicle to reach the maximum efficiency as the parameters are fixed (Lin *et al*., 2003). Rimaux *et al*. (1999) and Mansour and Coldic (2012) proposed a global optimal strategy based on dynamic programming methods for parallel HEV and parallel-series HEV, respectively. These techniques can find the global optimal solution of the control parameters, such as the engine/motor torque, but do not offer an on-line solution because they assume that the future driving cycle is entirely known. Paganelli and Delprat (2002) proposed an instantaneous optimization control strategy based on the equivalent fuel consumption minimization method. The instantaneous optimization control strategy equals the energy consumed by the battery to fuel the thermal energy and considers the total fuel consumption at each time as the optimal target to solve for the control variables and to realize fuel consumption minimization at each time under unknown driving conditions. However, it is difficult to implement this EMS because it requires intensive computation and precious vehicle model. The fuzzy EMS proposed by Lee and others (Lee and Sul, 1998; Schouten *et al.*, 2002; Pu *et al.*, 2005) controls the hybrid powertrain using fuzzy logic, which does not require a mathematical

**Corresponding author.* e-mail: jinanwujian@163.com

model and has strong robustness and good real-time performance. However, the fuzzy controller is designed by human expertise, and thus it cannot find the optimal solution. Moreover, the studies above did not consider the effect of the driving conditions on the control strategy. The fuel economy cannot be satisfied when the driving condition changes (Langeri *et al*., 2005).

Many researchers have introduced the driving cycle information into the energy management of HEV in different methods. Gong *et al*. (2008) proposed the two-scale dynamic programming (DP) algorithm for a plug-in HEV associated with the driving cycle modeling based on intelligent transportation systems (ITS). By combining the past and predicted vehicle speeds and GPS data, an adaptive equivalent fuel consumption minimization strategy (A-ECMS) adopts a online adaptive algorithm for the estimation of the equivalence factors according to the current driving conditions and determines the control parameters that minimize the fuel consumption (Musardo *et al*., 2005). Moura *et al*. (2011) used stochastic dynamic programming methods to optimize the HEV energy management over a distribution of driving cycles, whose model is a stochastic component of the plant model, which predicts the distribution of future energy demands using a discrete-time Markov chain. Murphey *et al.* (2012) combined dynamic programming with machine learning to predict driving environments and generated an optimal power split for a given driving environment. These results show that the prediction of the driving cycle is meaningful research and could be very important to improve the fuel economy of HEV.

In this paper, a fuzzy EMS based on driving cycle recognition is proposed to improve the fuel economy of PHEV. The EMS can recognize the driving cycle based on learning vector quantization (LVQ), and the fuzzy torque distribution controller selects the corresponding membership functions and rules to control the hybrid system according to the identification results of the driving cycle recognition. The simulation results show that the fuzzy EMS based on driving cycle recognition can effectively reduce the fuel consumption substantially compared with traditional fuzzy EMS.

2. OPERATING MODES OF PHEV

A parallel style powertrain is used in this study for a PHEV, and the configuration is schematically shown in Figure 1. The internal combustion engine and the electric motor are combined together through a torque combination device. Both the engine and the motor can supply driving torque to propel the vehicle. In addition, the motor can also act in reverse as a generator for braking and to charge the batteries. Thus, in a PHEV, the size of the engine and motor is small. The engine can operate at a high efficiency range during most of driving time, and the battery capacity may be small depending on concrete requirements.

Because the engine and the motor have distinct efficient work areas, the operating modes of the vehicle should vary for different driving cycles. The operating modes of the PHEV can be roughly classified into five categories as follows;

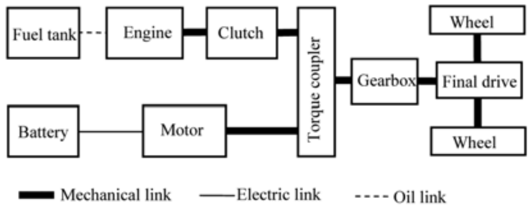

Figure 1. Parallel HEV configuration.

(1) The motor will supply all of the driving torque when the vehicle speed is below a certain minimum value or the required torque is smaller than a certain value.
(2) When the engine runs efficiently with the required driving torque at a given speed, the engine will produce the required torque to drive the vehicle alone, and the engine will drag the motor to replenish the battery according to the battery state of charge (SOC).
(3) The motor and engine propel the vehicle simultaneously when the required torque is greater, such as when the acceleration is greater than the maximum that can be produced by the engine at the operating speed of the engine.
(4) When the vehicle is running in idle mode and the battery SOC is lower, the engine will provide additional torque, which will be used by the motor to replenish the battery; otherwise, engine is turned off.
(5) The motor charges the batteries by regenerative braking if the battery SOC is lower than highest desired value.

In the last operating mode, the torque request of hybrid powertrain $T_r < 0$ and the EMS is simple. In four other operating modes, $T_r >= 0$, and the torque request is distributed between the engine and the motor as follows:

$$T_r = T_e + T_m \tag{1}$$

where T_r is determined by the driver pedal signal, the current vehicle speed and the gear ratio; and T_e and T_m are, respectively the torque of engine and motor. In this condition, the EMS of a PHEV must determine the optimum combination of the torque values from both the engine and the motor according to T_r, SOC and the control rules while battery charging is maintained.

3. CONFIGURATION OF EMS

By considering the effect of the driving cycle on EMS, a fuzzy EMS based on driving cycle recognition is proposed, which is composed of driving cycle recognition and a fuzzy torque distribution controller, as shown in Figure 2. The fuzzy torque distribution controller can determine the

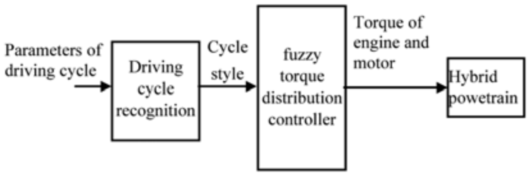

Figure 2. Schematic diagram of the EMS.

distribution of the driver torque request between the engine and the motor, and it has many groups of control parameters, such as the membership function and fuzzy rule sets, which are optimized offline by using particle swarm optimization (PSO) for six typical driving cycles. An improvement of the fuel economy performance can be achieved if the fuzzy torque distribution controller selects the right membership functions and fuzzy rules in accordance with the driving cycle. Thus, the EMS incorporates a driving cycle recognition module whose role is to identify the current driving cycle type. Based on the vehicle traveling parameters, the driving cycle recognition identifies the driving cycle style periodically, and then fuzzy torque distribution controller selects the corresponding membership functions and fuzzy control rules to distribute the torque between the engine and the motor reasonably.

4. DRIVING CYCLE RECOGNITION BASED ON LVQ NETWORK

The basic fuzzy torque distribution is driving cycle recognition, whose function is to classify the current driving situation in terms of some facility-specific driving cycles. To include urban, suburban and highway driving, three main driving cycles, NYCC, MANHATTAN, WVUSUB, CSHVR, US06_NWY and HWFET (shown in Figure 3), in ADVISOR software are chosen to represent six driving cycles, labeled driving cycle 1 to driving cycle 6. These six driving cycles are divided into three groups: two urban driving cycles (NYCC, MANHATTA), two suburb driving cycles (WVUSU, CSHV) and two highway driving cycles (US06_HWY, HWFET). Based on the vehicle traveling parameters, such as the maximum speed and the average speed, driving cycle recognition makes use of a LVQ network to identify the current road type correctly.

4.1. LVQ Network

LVQ is a supervised competitive network and has applied in pattern recognition and data compression successfully (Kohonen, 1990). Thus, the LVQ network is selected to classify the driving cycle type. The LVQ network is composed of three layers: the input layer, the competitive layer and the output layer. The structure of the LVQ network is shown in Figure 4.

In Figure 4, the input vector of the input layer is $X=[x_1,x_2,\ldots x_{10}]$; w_{ij} is the connective weight between the ith neuron of the competitive layer and the jth neuron of the

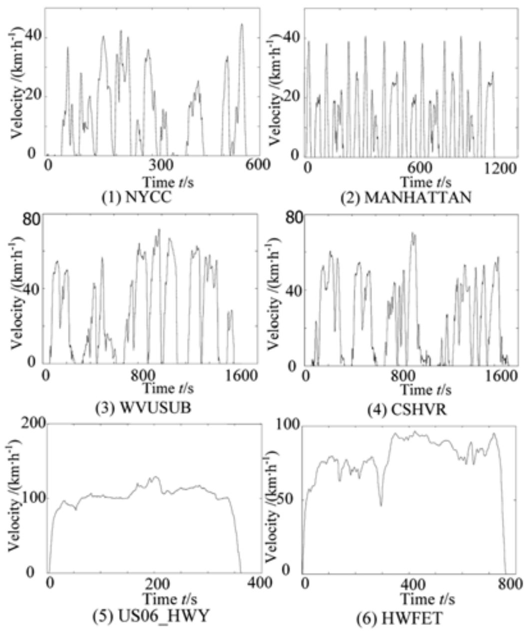

Figure 3. Six typical driving cycles.

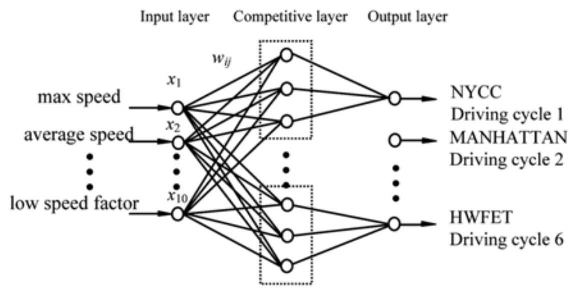

Figure 4. Structure of the LVQ neural network.

input layer. To identify the driving cycle, the ten features were extracted from the vehicle speed during the time interval, and the ten neurons of the input layer matched these ten characteristic parameters: maximum speed, average speed, maximum acceleration, average acceleration, maximum deceleration, average deceleration, idle time factor (idle time/total time), high speed factor (high speed time/total time), mid speed factor (mid speed time/total time) and low speed factor (low speed time/total time). The actual values of the ten features for the six driving cycles are presented in appendix A. The neurons of the competitive layer are used to classify the input vector into subclasses, and the linear output layer combines these subclasses into the appropriate target classes. The linear output layer has six neurons that represent six typical driving cycles, as shown in Figure 4. The number of competitive layer neurons is 60.

4.2. Training of the LVQ Network

As a mixed network, the LVQ combines the competitive learning and supervised learn algorithms, and thus classifica-

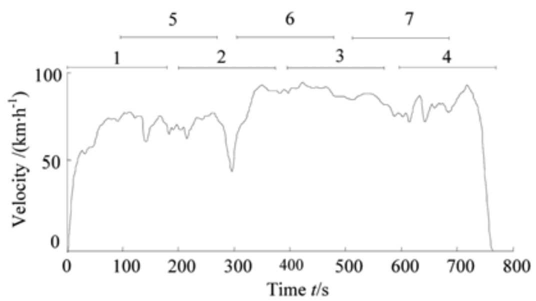

Figure 5. Training data generation.

tion information must be given as teacher signal in the learning process. The classification information, that is, the training samples, can be obtained based on characteristic parameters of the six typical driving cycles when the driving cycle is recognized. If only the characteristic parameters of whole driving cycle are taken as training samples, mistakes can be made easily because of the long cycles of the six driving cycle and the comparability in some short periods between every driving cycle. Therefore, it is preferable to divide each driving cycle into the appropriate number of 180-s overlapping shorter periods and then extract their characteristic parameters. The rationale here is that a typical (stop-go-stop) cycle in urban traffic situations is approximately 3 min (Langeri and Won, 2005). Thus, a value of 180 s is used in this study. Figure 5 shows the HWFET driving cycle divided into seven time periods; the ten characteristic parameters of the time periods, i.e., maximum speed, average speed, maximum acceleration etc., are extracted and considered as training samples that belong to the type of HWFET in the LVQ network.

Using this method, characteristic parameters of the six driving cycles in different periods are taken as training samples, whose category is pre-specified in the LQV. Then, the initial weights and the learned velocity are set, and the weights are corrected through supervised adaptive learning. The LVQ2 algorithm is adopted here to adjust the neuron weights. The algorithm is an iterative learning algorithm that performs "award-punish" according to the characteristics of the training samples. The weight vector of the neuron in the competitive layer is adjusted by encouraging weights that classify correctly while punishing weights that classify incorrectly. The steps of the algorithm are depicted below:

(1) Setting variables and parameters:
$W_i(n) = [w_{i1}(n), w_{i1}(n), \ldots, w_{i10}(n)]^{\mathrm{T}}$ is the weight vector, and n is iterative time, i=1,2, …,60;

(2) Initializing the weight vector $W_i(0)$ and the learning velocity $\eta(0)$;

(3) Selecting the input vector X from the training set;

(4) Adjusting the weight vector $W_i(n)$ according to The Kohonen rule:

If the victorious neuron represents the right classification, then

$$W_C(n+1) = W_C(n) + \eta(n)[X - W_C(n)] \tag{2}$$

Otherwise, the victorious neuron R that represents right classification is determined, and the weight is adjusted as

$$W_C(n+1) = W_C(n) - \eta(n)[X - W_C(n)] \tag{3}$$

$$W_R(n+1) = W_R(n) + \eta(n)[X - W_R(n)] \tag{4}$$

(5) Adjusting the learning velocity, which can be expressed as

$$\eta(n) = \eta(0)(1 - n/N) \tag{5}$$

(6) If the iteration time n is less than the maximum iteration time N, go to step (4). Otherwise, end the iteration.

After training, the weights of the neurons in the LVQ network reflect the statistical distribution of the training samples. Here, the LVQ network can be considered as driving cycle recognition. Ten characteristic parameters before this moment are collected punctually and used as the network input; then, the type of the present driving cycle can be determined.

5. FUZZY TORQUE DISTRIBUTION CONTROLLER

In addition to correctly recognizing the present driving cycle, to increase fuel economy of the HEV, it is necessary to design a proper torque distribution strategy of the hybrid powertrain for different driving cycles, which control the output torque of the engine and motor to realize different work modes of the hybrid powertrain and the dynamic switching between the work modes based on various real-time parameters, such as the required torque of the hybrid powertrain, the battery SOC and so on. A fuzzy torque distribution controller with variable parameters is proposed to achieve this goal.

5.1. Fuzzy Torque Distribution of PHEV

The fuzzy logic-based torque distribution of the hybrid powertrain does not rely on a precise mathematic model and has preferably robust properties. The realization of the fuzzy torque distribution relies on a fuzzy torque distribution controller that consists of three inputs and one output, as shown in Figure 6. The T_r and SOC is the input for the fuzzy control, the output is the engine torque T_e, the driving cycle type is the result of driving cycle recognition, and it is used to select the optimal membership function and control rule, i.e., the variable parameter, from the membership function and fuzzy rule sets. The numerical inputs are converted into linguistic fuzzy values. Then, given the fuzzy values and the already established rule base, the inference generates the linguistic control values. Because these linguistic inference results cannot be used in the

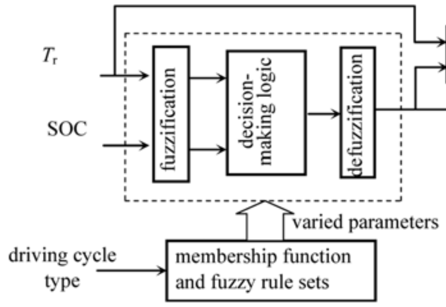

Figure 6. Configuration of the fuzzy torque distribution controller.

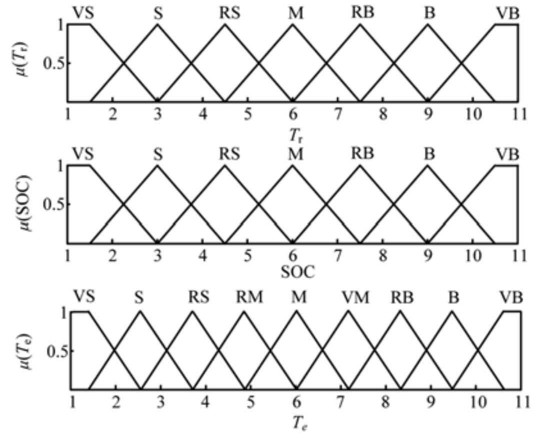

Figure 7. Membership functions of the input and the output.

actuator directly, these control values are converted into a numerical output in defuzzification, that is, the output torque of the engine T_e is obtained. Furthermore, the output torque of the motor is derived from T_r by subtracting T_e.

The fuzzy sets and membership functions of the inputs and output are shown in Figure 7, where T_r, SOC and T_e are all normalized from 1 to 11. The '1' of T_r corresponds to zero, '6' to the optimal torque determined based on the optimal efficiency-torque curve and speed of engine, '11' to the maximum engine torque, and the others to the torque through linear interpolation. The domain of the battery SOC corresponds to the SOC range (determined by the work efficiency of the battery), where '1' represents the minimum value, 0.5, and '11' represents the maximum value, 0.8. The membership functions of variables are overlapping symmetrical triangles and symmetrical trapezoids on the vertical axis, as shown in Figure 7. Seven fuzzy sets {VS, S, RS, M, RB, B,VB} of the input variable and nine fuzzy sets {VS,S,RS, RM,M, VM,RB,B,VB} of the output variable are defined. Here VS denotes very small, S is small, RS is rather small, RM is a value between rather small and medium, M is medium, VM is a value between medium and rather big, RB is rather big, B is big, and VB is very big.

Table 1. Control rule table.

T_r \ SOC	VS	S	RS	M	RB	B	VB
VS	RM	RS	RS	S	S	VS	VS
S	RM	RM	RS	RS	S	S	VS
RS	M	M	RM	RS	RS	S	S
M	RM	VM	M	M	M	RM	RS
RB	RB	RB	VM	M	M	RM	RM
B	B	B	RB	RB	VM	VM	M
VB	VB	B	B	RB	RB	VM	VM

The fuzzy control rule is another essential component in fuzzy logic-based torque distribution. The example of the control rule is shown in Table 1, which depends on the experience of experts. The form of the fuzzy control rule chosen according to the torque distribution of the hybrid powertrain is R^i: If a_1 is A_1^i and a_2 is A_2^i, Then u is B^i, $i = 1,2,\ldots m$ where R^i denotes the ith rule, a_i denotes the input vector and u denotes the output vector. $7 \times 7 = 49$ items of the fuzzy control rule are set, and the center of gravity method is applied to for defuzzification.

5.2. Fuzzy Controller Based on Particle Swarm Optimization

For the fuzzy torque distribution controller, if the determination of membership functions and fuzzy control rules depends on the experience of experts, the global optimal solution will not be obtained generally for biggish subjectivity. It is difficult to optimize using the gradient method and dynamic programming for the nonlinearity of the fuzzy control while PSO can implement effective search in a complex space because it is a stochastic global optimization approach based on swarm intelligence (Kennedy and Eberhart, 1995). In PSO, a population of particles is flown in multidimensional space to arrive at a position that can give an optimum solution. Each particle flies in the solution space with a velocity that is dynamically adjusted according to its flying experiences and those of its peers. The strength of the algorithm lies in its simplicity because it is easily coded and requires very few algorithm parameters to define convergence behavior. Therefore, to obtain different control parameters for different driving cycles, the PSO is applied to optimize the six groups of membership functions and fuzzy control rules of the fuzzy torque distribution controller based on six driving cycles to obtain an optimal fuzzy controller.

The first thing is to code the membership functions and fuzzy control rules of fuzzy torque distribution controller as optimized variables in the PSO. For the membership function of the required torque $\mu(T_r)$, as shown in Figure 8, its membership function set is symmetrical about the center of the domain, and the vertex of the membership function

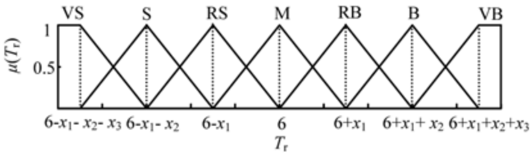

Figure 8. Optimized parameters of the membership function.

is shown in Figure 8. The membership function parameters that must be determined are real numbers x_1, x_2 and x_3 between [0,5]. The coordinates of the triangle and the trapezoid are ascertained by x_1, x_2 and x_3, which will be optimized by the PSO. The different membership functions of T_r in the fuzzy torque distribution controller are described by this method and the values of x_1, x_2 and x_3. The means to determine the membership function of the SOC and the engine torque are similar to $\mu(T_r)$, and the number of their optimization parameters are 3 and 4, respectively. Therefore, 10 membership function parameters must actually be determined. The fuzzy control rules adopted above could be considered as the permutation and combination of a group of fuzzy sets of input and output variables. When the sequence of the fuzzy sets of input variables are decided, the consequent part of fuzzy control rules are taken as the optimized variables. The fuzzy control rules are expressed as 49 integers between [1,9], where '1' represents the fuzzy set 'VS' of the output variable, '2' represents the fuzzy set 'S' of the output variable, and so on. The initial 10 dimensions of each particle position are optimized membership function parameters, which are encoded in float form. The remaining particle positions represent 49 fuzzy control rules and are encoded in integer form, denoted as y_1~y_{49}. The code of each particle position is shown in Figure 9.

Then, the total fuel consumption is taken as optimized objective, and six groups of membership functions and fuzzy control rules are obtained by combining the PSO algorithm and the ADVISOR software based on the off-line optimization with six typical driving cycles. As shown in Figure 10, the PSO algorithm modifies the optimized variables of the fuzzy torque distribution controller, i.e., the membership function and the fuzzy control rule, calls for the ADVISOR simulation runs in the drive cycle test and then obtains the evaluations of the objective values including the fuel consumption.

The optimization step of a group of optimal membership functions and fuzzy control rules for a given driving cycle can be stated as follows (Wu *et al.*, 2008):

(1) Initialize the positions and the associated velocities of all particles in the population randomly in the search space. The particle position represents the optimization variable in the fuzzy torque distribution controller.
(2) Evaluate the objective functions for the given driving cycle of each particle in the population by combining the PSO algorithm and the ADVISOR software.

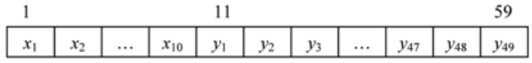

Figure 9. Code for each particle position.

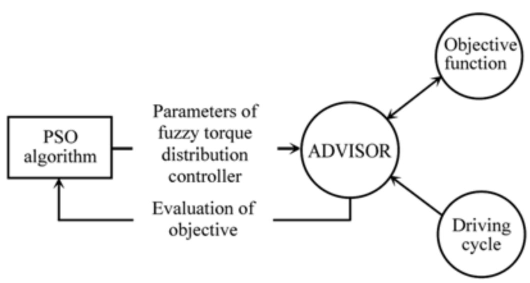

Figure 10. ADVISOR linkage with PSO.

(3) Calculate the fitness values of all particles according to fuel consumption and determine the individual extremum and the global extremum of the current generation.
(4) Update the new velocities and positions of each particle.
(5) Stop the program if the convergence criterion is satisfied; otherwise, go to step (2). The convergence criterion is that the fitness of the global extremum does not change for N iterations. Decode the global extremum and take the result as the parameters of the fuzzy torque distribution controller.

After the optimization for six typical driving cycles, the fuzzy torque distribution controller can select one corresponding group from the six groups of membership functions and fuzzy rules based on the result of driving cycle recognition to realize optimal torque distribution between the engine and the motor, i.e., the best torque distribution that fuzzy control can realize for HEV energy management.

6. SIMULATION RESULTS AND ANALYSIS

To validate the fuzzy EMS based on driving cycle recognition, the vehicle simulation model is constructed on the basis of ADVISOR, whose configuration is shown in Figure 1. The simulation parameters of the main components are listed in Table 2.

By combining the method described above and the off-line optimization of the six typical driving cycles, NYCC, MANHATTA, WVUSU, CSHV, US06_HWY and HWFET, the LVQ network and the fuzzy torque distribution controller are found and used in the EMS. The simulation of the EMS is conducted for the UDDS and UNIF01 driving cycles based on ADVISOR, and the results are compared with four types of fuzzy EMS without driving cycle recognition.

Two time factors should be defined in the simulation. The term T_{it} is used to indicate when the driving cycle type

Table 2. Basic parameters of the hybrid electric vehicle.

Vehicle	Mass m/kg	1 090
	Frontal projection area A/m^2	2.1
Motor	Type	AC
	Maximum power P_{max}/ kW	20
Battery	Type	Nimh
	Capacity C/ (A·h)	6
	Voltage U/V	308
Engine	Displacement Q/L	1.0
	Maximum power P'_{max}/ kW	41

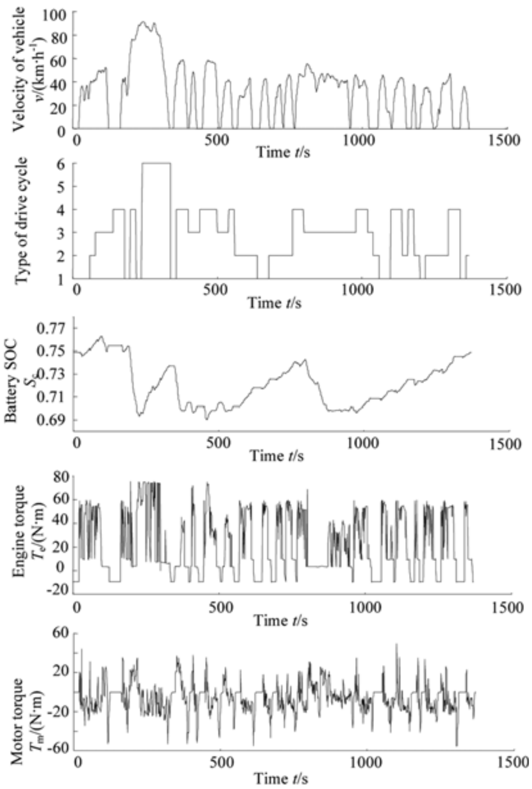

Figure 11. Simulation results for the UDDS driving cycle.

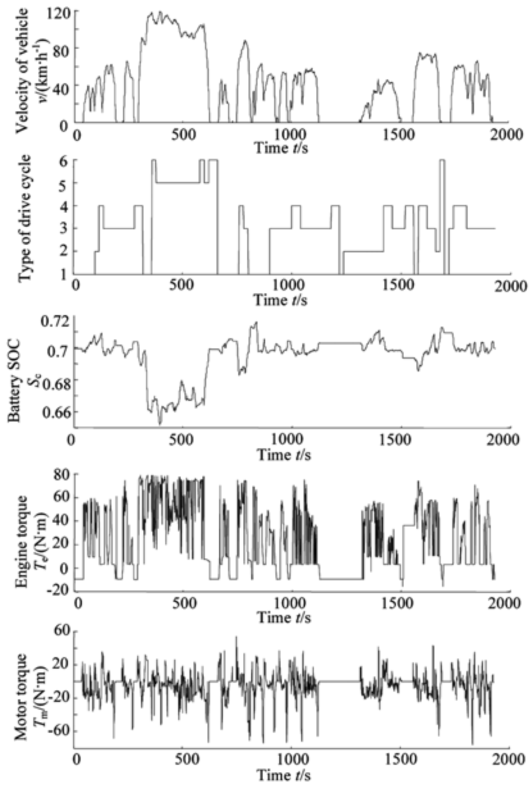

Figure 12. Simulation results for the UNIF01 driving cycle.

Table 3. Fuel economy of different EMS for various driving cycles.

Driving cycle	Fuel consumption (L/100 km)				
	F_EMS	PSO1	PSO2	PSO3	RI_EMS
UDDS	6.8	6.46	5.87	7.75	5.68
UNIF01	6.95	6.25	7.7	7.14	6.17
NYCC	17.2	14.2	15.77	15.29	14.2
WVUSUB	7.37	6.99	6.01	7.99	6.03
US06_HWY	6.95	6.97	8.06	6.7	6.75

is updated periodically. The term T_{lt} is the size of the time windows of the short term past driving history, and the driving data in the range of T_{lt} are used in driving cycle recognition. The parameter T_{it} is set to 5 seconds, and T_{lt} is set to 60 seconds in the simulation. In the process of simulation, the driving cycle 1 is used to select the membership functions and the fuzzy control rules for the NYCC driving cycle in the first T_{lt} seconds of driving. Subsequently, the LVQ network performs the driving cycle recognition task periodically (at every T_{it}) and feeds the driving cycle type information to the fuzzy torque distribution controller. In the fuzzy torque distribution controller, the membership functions and the fuzzy control rules paralleling the typical driving cycle are selected to control the powertrain at every T_{it}. The vehicle speed curve, the recognition results and the dynamic curve of the engine, motor and SOC for the UDDS and UNIF01 cycles using fuzzy EMS based on driving cycle recognition are described in Figure 11 and Figure 12. A comparison of the velocity curve of the six typical driving cycles with the two composite driving cycles clearly shows that our method can recognize the driving cycle correctly, and the figures show that the fuzzy EMS controls the output torque of the engine and motor reasonably well and maintains the battery SOC in a certain range.

Table 3 shows the comparison of the fuel consumption per one hundred kilometers for the traditional fuzzy EMS (F_EMS) and the optimized fuzzy EMS (PSO1, PSO2 and PSO3) for the NYCC, WVUSUB and US06_HWY driving cycles and proposed fuzzy EMS based on driving cycle recognition (RI_EMS). The test driving cycles include UDDS, UNIF01, NYCC, WVUSUB and US06_HWY in the ADVISOR software. The equivalent fuel consumption generated by the motor is considered in the simulation.

Table 3 shows that the optimized fuzzy EMS (PSO1, PSO2, PSO3) based on a given driving cycle has better fuel economy than other strategies but has poor fuel economy when used for other driving cycles. It is easy to understand that the optimized fuzzy EMS without driving cycle recognition cannot adapt to varied driving patterns. For UDDS and UNIF01, RI_EMS has better fuel economy than the other four strategies because it can adjust the fuzzy controller according to the result of driving cycle recognition. The result shows that RI_EMS can adapt to all types of driving cycles with better fuel economy. Furthermore, the RI_EMS has the advantage of fuzzy control, such as strong robustness and good real-time quality, and thus it is helpful to use the proposed EMS in practical HEV.

7. CONCLUSION

Because it is difficult to construct an accurate mathematical model of the vehicle and the driving cycle, a rule-based method is still the most feasible in the design of HEV EMS at present. A fuzzy EMS based on driving cycle recognition is proposed in this paper, and the strategy overcomes the disadvantage that the traditional fuzzy EMS cannot obtain optimal solutions. The simulation results using ADVISOR demonstrate that the fuzzy EMS based on driving cycle recognition can decrease fuel consumption more effectively than traditional fuzzy energy management strategies.

Only the vehicle fuel consumption is considered as the optimization objective in this paper and not the exhaust emissions. The work in the future is to consider both the exhaust emissions and the fuel consumption as the optimization objective. In addition, it has important effects on the performance improvement of the EMS to design the time interval T_{it} to recognize the driving cycle and the time interval T_{lt} to extract the characteristic parameters of the driving cycle properly, which requires further research.

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APPENDIX

Appendix A.

Table A. Recognition characteristics of the six typical driving cycles.

Driving cycle	max speed /(kmh^{-1})	average speed /(kmh^{-1})	max acceleration /(ms^{-2})	max deceleration /(ms^{-2})	average acceleration /(ms^{-2})	average deceleration /(ms^{-2})	idle time factor	low speed factor	mid speed factor	high speed factor
NYCC	44.58	11.41	2.68	-2.64	0.62	-0.61	0.35	0.23	0.02	0.00
MANHATTAN	40.72	10.98	2.06	-2.5	0.54	-0.67	0.36	0.28	0.00	0.00
WVUSUB	72.1	25.87	1.29	-2.16	0.33	-0.42	0.25	0.13	0.36	0.00
CSHVR	70.49	21.86	1.16	-1.79	0.39	-0.46	0.22	0.14	0.27	0.00
US06_HWY	129.23	97.91	3.08	-3.08	0.34	-0.41	0.03	0.01	0.03	0.85
HWFET	96.4	77.58	1.43	-1.48	0.19	-0.22	0.01	0.01	0.21	0.29

low speed factor=low speed time/total time, low speed is defined as a speed between 16.1 kmh^{-1} and 32.2 kmh^{-1};
mid speed factor=mid speed time/total time, mid speed is defined as a speed between 40.26 kmh^{-1} and 72.46 kmh^{-1};
high speed factor=high speed time/total time, high speed is defined as a speed higher than 88.57 kmh^{-1}.