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Research Article

Research of Ant Colony Optimized Adaptive Control Strategy for Hybrid Electric Vehicle

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Energy management control strategy of hybrid electric vehicle has a great influence on the vehicle fuel consumption with electric motors adding to the traditional vehicle power system. As vehicle real driving cycles seem to be uncertain, the dynamic driving cycles will have an impact on control strategy's energy-saving effect. In order to better adapt the dynamic driving cycles, control strategy should have the ability to recognize the real-time driving cycle and adaptively adjust to the corresponding off-line optimal control parameters. In this paper, four types of representative driving cycles are constructed based on the actual vehicle operating data, and a fuzzy driving cycle recognition algorithm is proposed for online recognizing the type of actual driving cycle. Then, based on the equivalent fuel consumption minimization strategy, an ant colony optimization algorithm is utilized to search the optimal control parameters "charge and discharge equivalent factors" for each type of representative driving cycle. At last, the simulation experiments are conducted to verify the accuracy of the proposed fuzzy recognition algorithm and the validity of the designed control strategy optimization method.

1. Introduction

Combined with the feature of traditional gasoline vehicle and pure electric vehicle, hybrid electric vehicle (HEV) improves the fuel economy and emission performance while sustaining enough travel distance, and it has become an important development direction of automotive industry [1]. If the energy management control strategy of HEV can realize the reasonable distribution between the vehicle-mounted multiple energy power sources, the fuel economy and emission would be improved, the lifetime of power battery would be extended, and the vehicle maintenance cost would be minimized under the requirement for vehicle dynamic performance [2, 3].

Early energy management control strategy of HEV includes rule-based strategies and optimization-based strategies [4]. Most of them are usually based on the fixed control parameters that could not adapt the dynamic driving cycles [5–7]. The actual energy saving effect seems to be unsatisfactory. Later, researchers find that the fuel consumption and emissions are sensitive to the driving cycle variation, and they start to study driving cycle recognition and adaptive control strategies in two aspects. One is using global position system (GPS), car navigation system, car to car communication, and other approaches to acquire the future road and traffic information such as average vehicle speed, road grade, and turning radius and then obtain the approximate global optimal energy distribution principles through the dynamic programming or other optimization algorithms [8]. But this kind of method needs a complex hardware implementation, and the global optimization needs large calculating quantity which may lead to a poor real-time performance. There is difficulty in its popularization and application. Another aspect of research is utilizing pattern recognition technology to identify the current type of driving cycle, according to the vehicle state parameters in the past period of time, such as average speed, idle time, and maximum acceleration [9]. It is relatively easy to implement, and this research method is selected to develop the adaptive control strategy in this paper.

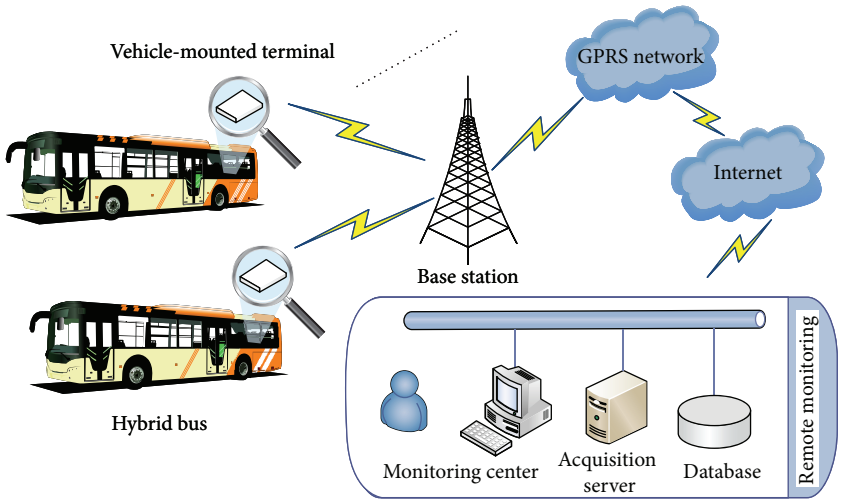


Figure 1: Remote data acquisition and monitoring system for HEV.

At present, the research on driving cycle recognition mainly contains neural network, support vector machine (SVM) and other predictive methods. Engström and Victor [10] proposed a statistical pattern recognition framework to analyze the collected vehicle operating data and utilized feed-forward neural network to classify the actual driving cycle into four types which are highway, arterial road, suburban, and urban, respectively. But the neural network-based method required a large number of suitable training samples to obtain a relatively accurate recognition result. Watanabe and Katsura [11] proposed an SVM driving cycle recognition method; it was suitable for the two-class classification problem, but it was more difficult to solve the multiclass classification problems. Gong et al. [12] proposed an iterative Markov chain approach for generating velocity profiles, which represent the specific driving pattern well based on the comparison of the phase plot to the typical real driving cycle. In this paper, a fuzzy driving cycle recognition algorithm is proposed to lay the foundation for the control strategy's adaptive adjustment.

The optimal control parameters in different types of driving cycles need to be determined after realizing the driving cycle recognition. The control parameters in present researches are mainly selected discretely according to the engineering experience, and then a relatively optimal solution is obtained through the simulating calculation; the parameter optimization result has the potential to be improved. Generally the optimization algorithm would be used to solve this kind of parameter optimization problem. As HEV is a strongly nonlinear complicated system, it takes a large amount of time for calculating the objective function according to the vehicle model; the optimization algorithm should have a fast convergence speed. Therefore, intelligent optimization algorithms such as genetic algorithm [13, 14], particle swarm optimization [15, 16], and simulated annealing algorithm [17] are introduced to solve such parameter optimization problem. In recent years, swarm intelligence algorithm did well in solving travelling salesman problem (TSP) and other NP-complete problems [18–21], and it also has some applications in the field of optimal control research [22]. In this paper, utilizing the feature of automatic gain and accumulating the knowledge about search-space, we introduce an ant optimization algorithm to solve the HEV optimal control parameters in each type of driving cycle.

The rest of the paper is structured as follows. In Section 2, four types of representative driving cycles are constructed based on the actual vehicle operating data and a fuzzy driving cycle recognition algorithm is proposed for online recognizing the type of actual driving cycle. Section 3 introduces basic equivalent fuel consumption minimization strategy and studies the off-line control parameter optimization in different driving cycles based on the ant colony optimization method. Section 4 presents the simulation experiment results of the designed adaptive control strategy. Section 5 concludes the presented work.

2. Driving Cycle Classification and Recognition

To achieve the objective of making control strategy being able to adaptively adjust according to different types of driving cycles, the driving cycle classification and recognition should be implemented in advance. In this section, driving cycles are classified into four types and representative cycle for each type is built to reflect the geography and traffic features in different regions. Then, a fuzzy clustering center matrix and the corresponding relative membership degree function are defined to realize the driving cycle recognition.

2.1. Construction of Representative Driving Cycles. The classification and construction of four types of driving cycles are based on the independently developed remote data acquisition and monitoring system [23]; it has been operating for nearly five years, as shown in Figure 1. The original vehicle data are gathered from the hybrid electric buses on the Dalian Energy Efficient and New Energy Vehicle

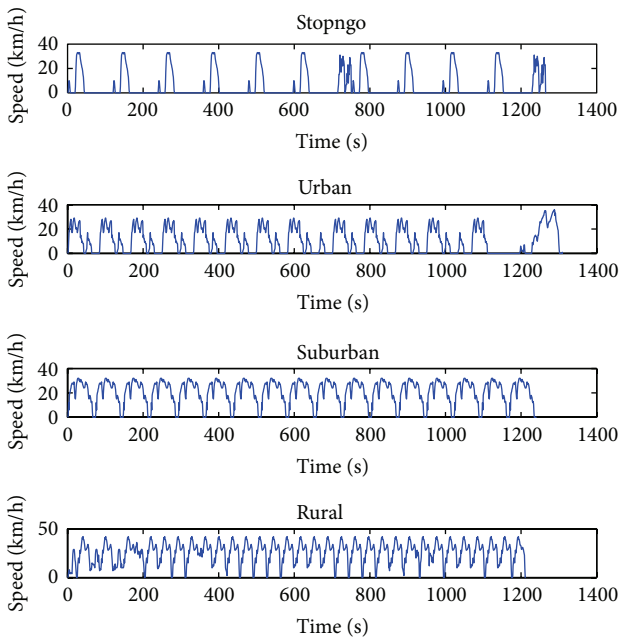


Figure 2: Four representative driving cycles.

Demonstration Project. A large number of reliable vehicle real-time operating data are collected from the Controller Area Network (CAN) bus through vehicle mounted terminal. The data can be divided into four types according to the city structure features; they are stopngo to represent the traffic jam cycles in the downtown, urban to represent the low speed flow in urban areas, suburban to represent the medium speed flow, and rural to represent the high speed flow in rural areas.

The steps for constructing four types of representative driving cycles are as follows. First, the microtrips are divided from the original vehicle speed data (microtrips are defined as a small driving trip segment from a vehicle idle point to the next idle point), and the database of the microtrips can be obtained from the original speed statistic database. Second, the characteristic parameters of each separate microtrip are calculated; the principal components and the corresponding contribution rate of these characteristic parameters can be obtained by the principal component analysis. Thus the cluster analysis technique is able to classify the microtrips into four cluster centers easily by theses principal components, and the microtrips which are nearest to the cluster center are chosen to construct the representative driving cycles. At last, four types of representative driving cycles are obtained by the linear combination of these selected microtrips. The results of the constructed four representative cycles are shown in Figure 2.

2.2. Fuzzy Recognition of Driving Cycle. The driving cycle recognition is based on the statistic characteristic parameters of actual driving cycle [24]; the commonly used cycle characteristic parameters are as follows: cycle average speed, average driving speed, maximum speed, mean acceleration, mean deceleration, maximum acceleration, maximum deceleration, idle time, the percentage of idle time, number of stops, and so on. In this paper, average cycle speed V_m, average driving speed V_{mr}, average deceleration A_d, average acceleration A_a, and percentage of idle time η are selected as the characteristic parameters for fuzzy recognition of driving cycle.

The sample driving cycle segment characteristic vector need to be recognized is expressed as $x = \{V_m, V_{mr}, \eta, A_a, A_d\}^T$. Together with four groups of parameters of the typical driving cycle constructed in Section 2.1, the characteristic vector is assembled as a matrix $X_{5\times5}$ to be identified:

$$X = \begin{bmatrix} V_m & 5.69 & 10.66 & 20.67 & 24.55 \\ V_{mr} & 19.59 & 16.55 & 23.22 & 27.27 \\ \eta & 0.7093 & 0.3562 & 0.1096 & 0.0998 \\ A_a & 1.34 & 0.70 & 0.71 & 0.94 \\ A_d & -0.88 & -0.76 & -0.65 & -1.13 \end{bmatrix} = (x_{ij})_{5\times5}. \quad (1)$$

As characteristic vector elements V_m, η, A_a are different in physical dimensions, the matrix to be recognized $X_{5\times5}$ should be normalized; the elements to be identified in the normalized matrix are expressed as $(r_{ij})_{5\times5}$, which are calculated as follows:

$$r_{ij} = \frac{x_{ij} - x_{i\min}}{x_{i\max} - x_{i\min}}. \quad (2)$$

Five index characteristic values of the four representative driving cycles make up the clustering center of the driving cycle class. After normalization it can be expressed as standard fuzzy clustering center matrix $(s_{ih})_{5\times4}$ in the fuzzy recognition:

$$S = \begin{bmatrix} 1.0000 & 0.7365 & 0.2057 & 0.0000 \\ 0.7478 & 1.0000 & 0.3778 & 0.0000 \\ 0.0000 & 0.5793 & 0.9839 & 1.0000 \\ 0.0000 & 1.0000 & 0.9844 & 0.6250 \\ 0.2500 & 0.7708 & 1.0000 & 0.0000 \end{bmatrix} = (s_{ih})_{5\times4}. \quad (3)$$

As characteristic parameters have different impact in the process of driving cycle fuzzy recognition, different weights of characteristic parameters need to be considered. So a characteristic indicator weight vector is defined as $W = (w_1, w_2, \ldots, w_5)$ which should satisfy the constraint conditions of $w_1 + w_2 + w_3 + w_4 + w_5 = 1$. In this paper, the characteristic indicator weight vector is selected as $W = (0.44, 0.34, 0.10, 0.09, 0.03)$.

After the initialization above, the relative membership degree u_{hj} of sample x_j to the category h $(h = 1, 2, 3, 4)$ is calculated as follows:

$$u_{hj} = \frac{1}{\sum_{k=1}^{c}\left(\sum_{i=1}^{m}\left[w_i(r_{ij} - s_{ih})\right]^2 / \sum_{i=1}^{m}\left[w_i(r_{ij} - s_{ik})\right]^2\right)}. \quad (4)$$

So the sample driving cycle segment x_j is recognized as the driving cycle type h which has the maximum relative membership degree u_{hj}.

3. Control Parameter Optimization Based on Ant Colony Algorithm

3.1. Basic Equivalent Fuel Consumption Minimization Strategy. The basic energy management control strategy to be optimized in this paper is ECMS. Its main idea is to multiply the battery electricity consumption by an equivalent factor α and transfer this electric energy to an equivalent vehicle instantaneous fuel consumption. In every computing interval t, the total equivalent fuel consumption to be calculated is the sum of drive motor's electric equivalent fuel consumption and actual engine fuel consumption, which is shown as follows:

$$\dot{m}_{\text{eq}} = \dot{m}_m + \dot{m}_e, \tag{5}$$

where $\dot{m}_{\text{eq}}$ is the total equivalent fuel consumption mass flow, in kg/s, and $\dot{m}_e$ is the actual engine fuel consumption mass flow which can be calculated as follows:

$$\dot{m}_e = \frac{P_e}{\eta_e \cdot Q}, \tag{6}$$

where P_e is the engine output power, η_e is the engine working efficiency, and Q is the fuel low caloric value, in J/kg.

$\dot{m}_m$ is battery's electric equivalent fuel consumption mass flow; as the actual power consumption of battery is electricity, it should be converted to the equivalent fuel consumption through the following equations:

$$\dot{m}_m = \begin{cases} \alpha_{\text{dis}} \cdot \dfrac{P_m}{Q} \cdot \dfrac{1}{\eta_{\text{dis}}} \cdot \dfrac{1}{\eta_m}, & P_b > 0 \\ \alpha_{\text{chg}} \cdot \dfrac{P_m}{Q} \cdot \eta_{\text{chg}} \cdot \eta'_m, & P_b < 0, \end{cases} \tag{7}$$

where P_m is the motor output power, when motor works as a generator it was a negative value; η_{dis} is the battery discharge efficiency; η_{chg} is the battery charge efficiency; η_m is the motor drive efficiency; η'_m is the motor generating efficiency; α_{dis} is the discharge equivalent factor; α_{chg} is the charge equivalent factor.

In (5) the calculated battery equivalent fuel consumption is not related to the current battery State of Charge (SOC); the strategy cannot ensure the battery SOC maintaining around a nominal value and get an acceptable battery efficiency to preserve battery life. Therefore the motor equivalent fuel consumption needs to be penalized with a nonlinear function to control the fluctuation range of SOC and ensure the battery charge balance. Firstly, SOC value in every simple time t needs to be normalized as follows:

$$x_{\text{SOC}}(t) = \begin{cases} -1, & \text{SOC}(t) \le \text{SOC}_{\min} \\ \dfrac{\text{SOC}(t) - \left(\left(\text{SOC}_{\max} + \text{SOC}_{\min}\right)/2\right)}{\left(\left(\text{SOC}_{\max} - \text{SOC}_{\min}\right)/2\right)}, & \text{SOC}_{\min} < \text{SOC}(t) < \text{SOC}_{\max} \\ 1, & \text{SOC}(t) \ge \text{SOC}_{\max}, \end{cases} \tag{8}$$

where $\text{SOC}_{\max}$ and $\text{SOC}_{\min}$ are the battery SOC working range. To maintain the SOC balance, if the SOC is in a lower stage, penalty function should enlarge the motor equivalent fuel consumption $\dot{m}_m$ to increase the cost of battery discharge and decrease the battery charge cost. Therefore the penalty function of SOC is selected as S-shape high order polynomials:

$$\beta(\text{SOC}) = 1 + 1.2\left(x_{\text{SOC}}(t)\right)^4 - 2\left(x_{\text{SOC}}(t)\right)^5. \tag{9}$$

Finally, the basic equivalent fuel consumption minimization control strategy can be simplified to an optimization problem in each instantaneous sample time:

$$J_{\min} = \min\left(\beta \cdot \dot{m}_m + \dot{m}_e\right). \tag{10}$$

s.t.

$$\begin{gathered} P_{\text{req}}(t) = \left(P_e(t) + P_m(t)\right)\eta_t, \\ P_{m\_\min}(t) \le P_m(t) \le P_{m\_\max}(t), \\ P_{e\_\min}(t) \le P_e(t) \le P_{e\_\max}(t), \\ P_{b\_\min}(t) \le P_b(t) \le P_{b\_\max}(t), \end{gathered} \tag{11}$$

where $P_{\text{req}}(t)$ is the driver's instantaneous power demand; η_t is the drivetrain's working efficiency; motor output power $P_m(t)$ and engine output power $P_e(t)$ should be within a certain range constrained by the constraint of current operating speed and battery SOC. The electric motor output power $P_m(t)$ is selected as a control variable. Thus, the $P_m(t)$ which satisfy the constraint conditions and make the objective function minimum can be solved to determine the motor and the engine working point.

3.2. Parameter Optimization Problem. In the above ECMS methods, selection of discharge equivalent factor α_{dis} and charge equivalent factor α_{chg} will directly affect the vehicle's utilization of electric energy and eventually have an impact on vehicle fuel economy. For example, in a congested urban driving cycle, a smaller equivalent factor will make vehicles tend to consume electric energy and reduce the engine working at a low speed with lower efficiency and higher emission. Therefore, according to the driving cycle recognition result, the optimal charge and discharge equivalent factors need to be determined under each type of driving cycle. It means that parameters of the basic control strategy need to be optimized to adaptively adjust for a better fuel economy without losing power performance.

Currently, the widely used control parameter calculation method is realized by setting a number of disperse

experimental values and then adjusting the parameter with trial and error method. And this calculation method always relies on the engineering experience. Although this method is practical, it cannot achieve the best efficiency of the power system. Therefore, it is necessary to introduce an optimization method to optimize HEV control parameters.

However, classic optimization methods generally require the objective function to be continuous and differentiable, and the sawtooth phenomenon leading to a slow convergence may occur while approaching the optimal solution. HEV is a complicated nonlinear system; in its control parameter optimization problem, it is difficult to find the optimal solution rapidly by using these classic optimization methods. Thus, this paper proposed an ant colony HEV control parameter optimization method to optimize the charge and discharge equivalent factor in each type of driving cycle, respectively. It has features of parallelism and positive feedback, and it can make full use of the vehicle model information.

This HEV control parameter optimization problem is to search the best solution for the objective function which minimizes the overall fuel energy consumption in every representative driving cycles constructed in Section 2. But as the charge and discharge equivalent factors are varied in the parameter optimization, the electric energy consumption under different parameters should be assessed according to a unified standard. Therefore we use the battery average efficiency $\overline{\eta}_b$, motor average efficiency $\overline{\eta}_m$, and transmission system average efficiency $\overline{\eta}_t$ to convert the battery energy consumption to the oil consumption; it can be expressed as follows:

$$\dot{m}_b = \frac{\Delta P_b}{\overline{\eta}_b \overline{\eta}_m \overline{\eta}_t}. \tag{12}$$

Then the objective function, total equivalent fuel energy consumption can be expressed as

$$\min F(X) = \int_0^t \left(\dot{m}_e + \dot{m}_b\right) dt, \tag{13}$$

where X is the control parameters "charge and discharge equivalent factors" to be optimized under each type of driving cycle; generally its value range is from 2 to 3.5. This optimization problem should satisfy the constraint of driving cycle's real-time speed requirement. The objective function value is the integration of total equivalent fuel consumption mass flow in (5) at every sample moment of the driving cycle to be optimized. Rules for ant colony parameter optimization are as follows.

(1) Ant Initialization. Randomly distribute the given number of M ants in a certain position of the variable definition domain $[a, b]$; each ant i is positioned as follows:

$$x(i,k) = a(k) + \frac{b(k) - a(k)}{M}(i - 1 + \text{rand}), \tag{14}$$

where rand is a random number between $[0, 1]$.

The initial pheromone quantity of each ant's position can be expressed as

$$\Delta\tau_{X(i)} = e^{-F(X_i)}, \tag{15}$$

where $F(X_i)$ is the objective function value of ant i.

(2) Ant Travelling Rules. After all the ants accomplish a searching process, one of them will find an optimal position in the current loop which will be the transfer guide for the rest ants' travelling in the next loop. So the ants transfer can be divided into two parts, one is the global search for the ants that have not found the optimal solutions moving towards the optimal solution $X(\text{Best})$, its transfer probability and step length is related to the amount of pheromone and relative positions of $X(i)$ and $X(\text{Best})$; the transfer probability is calculated as follows:

$$P_{i,\text{Best}} = \frac{e^{(\tau_{X_{\text{Best}}} - \tau_{X_i})}}{e^{\tau_{X_{\text{Best}}}}}. \tag{16}$$

When ant i moves to a large quantity of pheromone information position, it may find a better optimized solution. Thus the transfer step length of ant i is defined in (16) when it is moving to the best position $X(\text{Best})$:

$$X_i = \begin{cases} X_i + \lambda\left(X_{\text{Best}} - X_i\right), & P_{i,\text{Best}} < P_o \\ X_i + \text{rand}(-1, 1) * \dfrac{b-a}{M}, & \text{otherwise}, \end{cases} \tag{17}$$

where $0 < \lambda < 1$, $0 < P_0 < 1$.

Another part of ants transfer is local search of the Best ant. It randomly searches for a better solution in a small determined neighborhood. The search radius decreases with the increase of iterations to find a more accurate solution in the later search period. The rules for local search are shown as follows:

$$X_{\text{Best}} = \begin{cases} X_{ls}, & F\left(X_{ls}\right) < F\left(X_{\text{Best}}\right) \\ X_{\text{Best}}, & \text{otherwise}, \end{cases}$$

$$X_{ls} = \begin{cases} X_{\text{Best}} + \omega \cdot \dot{r}, & \text{rand}(1, 1) < 0.5 \\ X_{\text{Best}} - \omega \cdot \dot{r}, & \text{otherwise}, \end{cases} \tag{18}$$

$$\omega = 1 - 0.4 \cdot \frac{i_{\text{ter}}}{n_{\max}},$$

where i_{ter} is the current number of iterations and $n_{\max}$ is the maximum iteration number.

(3) Pheromone Update Rules. When the global and local search are finished, the pheromone information of every ants' position needs to be updated as follows:

$$\tau_{X(i)} = \rho \cdot \tau_{X(i)} + \Delta\tau_{X(i)}, \tag{19}$$

where ρ is the pheromone volatilization coefficient and $0 < \rho < 1$, $\Delta\tau_{X(i)}$ is calculated in (14).

(4) Solve Procedure of Parameter Optimization. The HEV control parameter optimization solving procedure is as follows.

(a) Determine the maximum iteration numbers $n_{\max}$, the ant colony size M, and the value range of control parameter X.

(b) Initialize current ant colony position and the corresponding pheromone quantity according to (14)-(15).

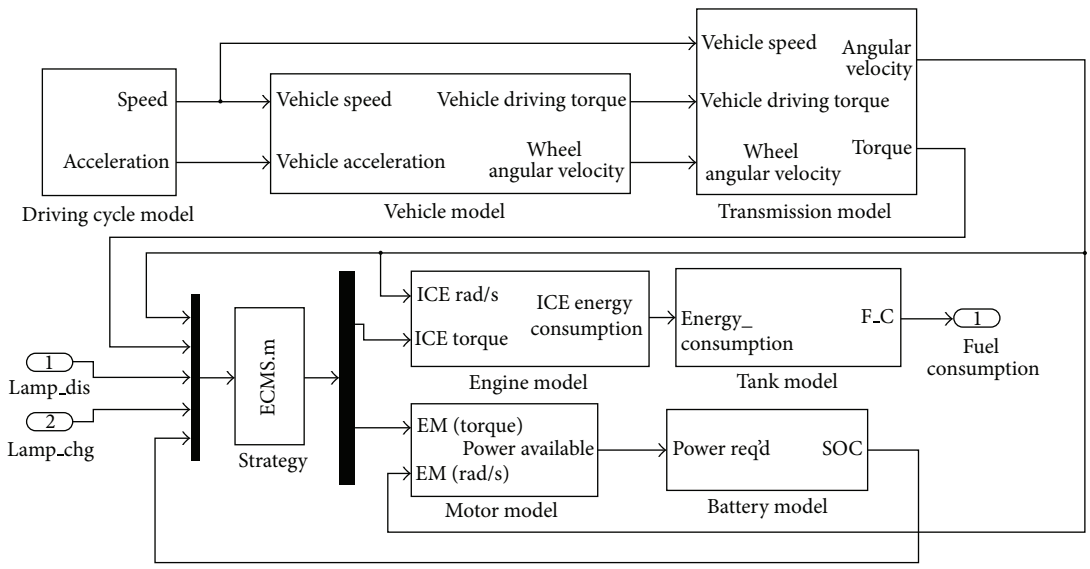


Figure 3: The hybrid electric bus fuel consumption simulation model.

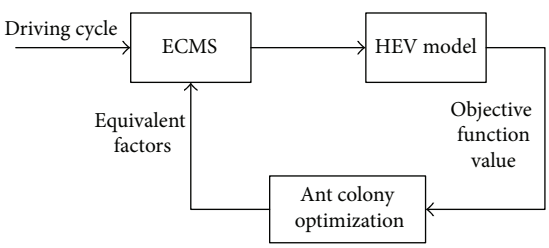


Figure 4: The parameter optimization process.

(c) Determine the ant at the optimal position X_{Best} according to the object function.

(d) The ants that did not find the optimal solutions conduct the global search to update ants' position according to (16)-(17).

(e) The ant at the optimal position X_{Best} does the local search and updates optimal position according to (18).

(f) Update the pheromone information with (19).

(g) If the termination condition is satisfied which means $i_{\text{ter}} \geq n_{\max}$, then finish the loop and output the optimal solution; otherwise go to step (c).

4. Simulation and Analysis

The ant colony control parameter optimization algorithm is realized by a Matlab m-language program. The relevant parameter settings are as follows: maximum iteration numbers $n_{\max} = 15$, ant colony size $M = 30$, control variables charge, and discharge equivalent factors value range $X_1, X_2 \in [1.5, 3.5]$, $\lambda = 0.3$, $\rho = 0.95$.

The optimized object is a parallel hybrid electric bus in this paper; its basic power component's technical parameters are shown in Table 1.

Table 1: The parameters of HEV.

Engine	DUETZ BF6M2012-22E4
Motor (PMSM)	Speed (rated/peak): 3600/6500 rpm Power (rated/peak): 30/90 kW Torque (rated/peak): 80/240 N·m
Ni-MH battery	Capacity: 40 Ah Number of modules: 28 Nominal voltage: 12 (volt/module)
AMT	5 speed, ratio: 5.785, 3.038, 1.623, 1.00, 0.773
Vehicle	Curb weight: 12000 kg Size: 11996 × 2550 × 3174 (mm)

The objective function Equation (12) is evaluated through a Matlab/Simulink model. According to the features of hybrid powertrain and ECMS control method, the vehicle fuel consumption simulation calculating model is constructed, as shown in Figure 3.

The input of this simulation model is the four representative driving cycles constructed in Section 2, respectively, and the control parameters charge and discharge equivalent parameters are adjusted by the ant colony optimization algorithm. While the algorithm's termination condition is satisfied, the objective fuel consumption calculated by the model will be minimized under the corresponding driving cycle. The parameter optimization process is shown in Figure 4.

With the control parameters varied in the iteration, the objective function equivalent oil consumption convergence procedure in four different types of driving cycles are shown in Figure 5. In this procedure, the ant algorithm adjusts the power distribution between engine and motor by changing the value of charge and discharge equivalent factors, so as to release and recover the electric energy more reasonable and effective, and to optimize the engine working range while making the objective function converge to the optimal value.

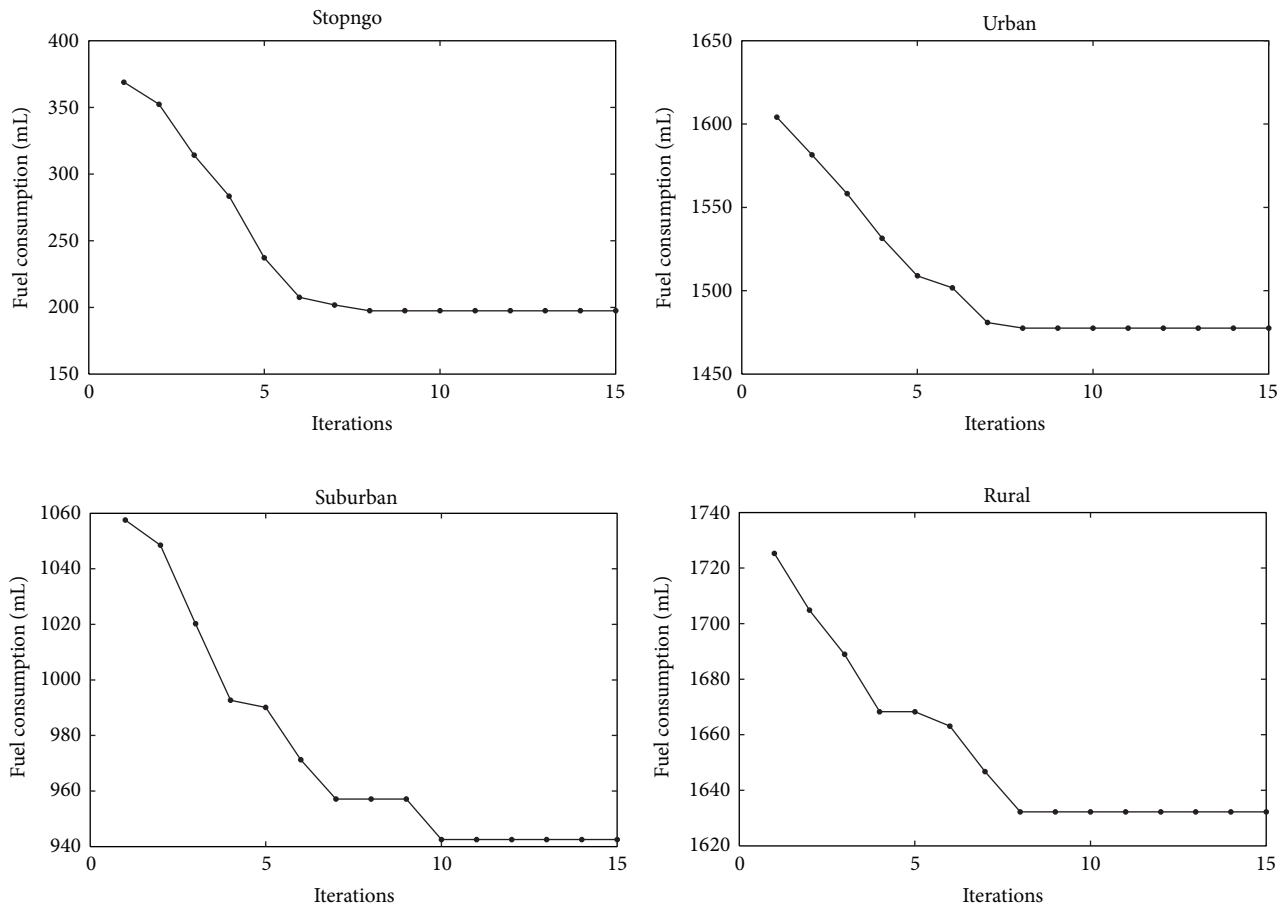


Figure 5: The objective function converge procedure in ant colony optimization.

Table 2: The optimal control parameters corresponding to each typical driving cycle.

The name of driving cycles	Charge equivalent factor	Discharge equivalent factor
Stopngo	1.52	2.27
Urban	1.56	2.52
Suburban	1.91	3.28
Rural	2.56	3.31

The final optimal value of charge and discharge equivalent factors under each driving cycle is shown in Table 2.

In order to achieve the purpose of making basic ECMS have the ability of adaptive adjustment with driving cycle and greatly improving the vehicle performance, an adaptive scheme of optimized ECMS is designed in this paper as shown in Figure 6.

The optimal control parameters and driving cycle recognition part are added into the hybrid electric bus Simulink strategy model (as shown in Figure 3) to test the control strategy's performance. The driving cycle tested in the process of simulation is the Dalian cycle (as shown in Figure 7(a)). It is constructed based on a real-time operating database which was collected from the hybrid electric buses in Dalian for four years by the remote vehicle-mounted data acquisition system for new energy vehicle. The total cycle time is 1235 s and it can reflect the actual geographical and traffic features of the Dalian area.

While Dalian driving cycle is inputted to the HEV Simulink model, the strategy module could receive vehicle speed information from the driving cycle module. The codes in the strategy module's Matlab m-file which realized the driving cycle recognition algorithm proposed in Section 2 calculate the relative membership degree u_{hj}. Thus the driving cycle type of microtrips in the recognition period can be identified, and the optimal equivalent factors can be updated in the strategy module realizing the adaptive ECMS scheme as shown in Figure 6. The recognition period is set to be 10 s in this paper. Recognition results are shown in Figure 7(b). Types 1, 2, 3, and 4 represent stopngo, urban, suburban and rural, respectively. From the recognition results, we can see that the driving cycle type can be identified well; speed and other characteristic parameter values are in accordance with the corresponding recognized representative cycle. The real driving conditions in the Dalian area can be reflected.

Basic ECMS control method is simulated as a contrast to the optimized adaptive control strategy. This paper is mainly studying the effect of charge and discharge equivalent

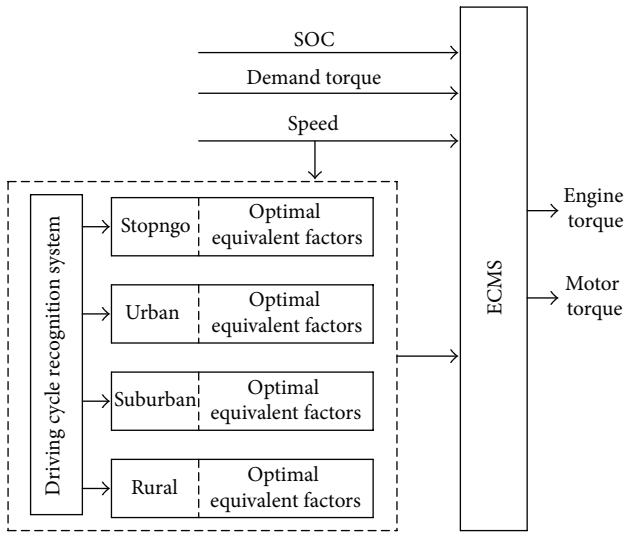
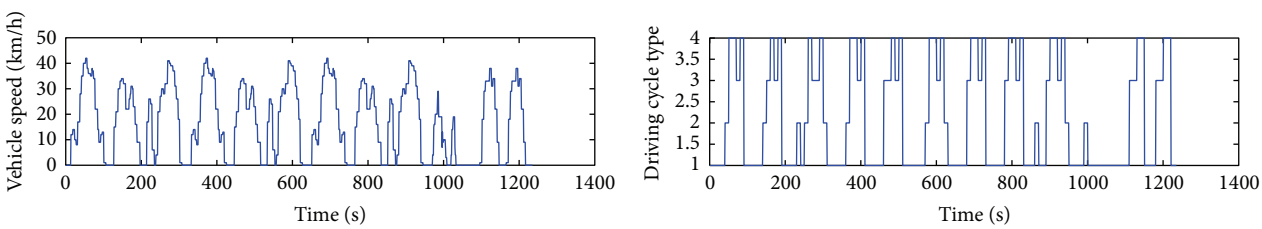


Figure 6: The adaptive ECMS scheme.



(a) Driving cycle of Dalian

(b) Cycle recognition result

Figure 7: The driving cycle of Dalian and its recognition result.

factors on the fuel economy, and the vehicle fuel economy performance results are determined by the energy power distribution between engine and motor, so the battery power curve in the whole cycle is the best way to express the energy distribution and the utilization of electric power. The contrast of the battery power curve between basic ECMS and optimized adaptive strategy is shown in Figure 8. From the result we can see that for the adaptive control strategy battery charge and discharge are fewer under middle high speed than those frequent battery charge and discharge in the basic ECMS. It is because that the charge equivalent factor is smaller. The discharge equivalent factor is larger in the middle high speed urban and suburban driving cycles under the optimized adaptive ECMS, and the cost to charge and discharge is large for the objective function of ECMS. As a result, the vehicle tends to use more engines to power the vehicle and reduce the battery charge and discharge. On the other hand, the adaptive control strategy tends to discharge more at a lower speed and charge more at a higher speed; it is also the consequence of the equivalent factor's adjustment under rural and stopngo driving cycles.

The fuel consumption and SOC variation curves are shown in Figure 9; it shows that the adaptive control strategy proposed in this paper has a better fuel economy with a bit lower final SOC; the engine oil consumption is 14% lower than the basic ECMS.

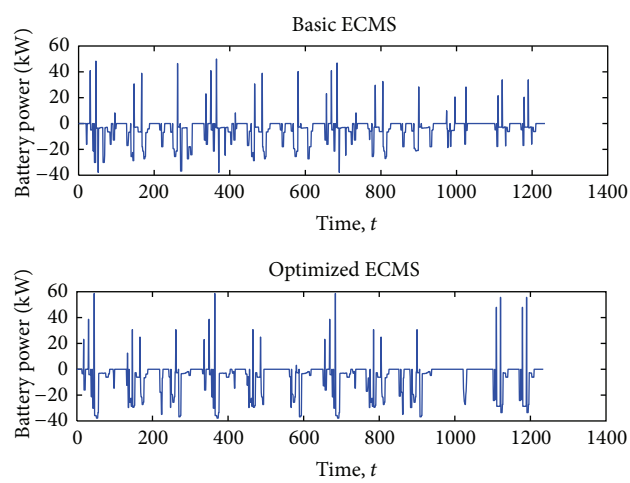


Figure 8: Battery power comparison of two control strategies.

5. Conclusion

In this paper, control strategy of HEV is further researched on the basis of remote data acquisition and monitoring system. Then an adaptive control strategy based on the ant colony parameter optimization for HEV is proposed. It can

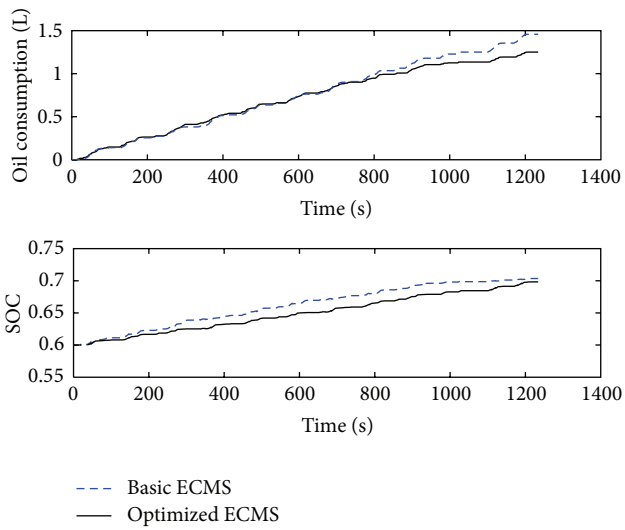


Figure 9: Oil consumption and SOC comparison curve.

adaptively adjust the control parameters according to the real driving cycle, and it is effective in improving vehicle fuel economy of hybrid electric vehicle. The main work of this paper includes: four representative driving cycles are constructed according to the vehicle operating data for the past five years; a fuzzy driving cycle recognition algorithm based on a relative membership degree function is proposed; for online recognizing the type of actual driving cycle; for each type of driving cycle, the optimal control parameters corresponding to each type of driving cycle are determined by using an ant colony optimization method which can effectively shorten the control parameter's adjustment time in the HEV road test; the validity and accuracy of the algorithm are verified by the simulation experiments at last. The results show that according to the on-line driving cycle recognition, vehicle controller is adjusted to the corresponding optimal control parameters, which realized the control strategy adaptive adjust with the variation of actural driving cycles, and the proposed control method improves vehicle fuel consumption effectively.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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