Optimization of extended range electric vehicle energy management strategy via driving cycle identification

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Abstract. There are ambitious fuel consumption targets for the manufacturers of heavy-duty vehicles. For this reason, extended range electric vehicle (EREV) is a promising powertrain technology. However, the energy management strategy (EMS) is still an obstacle to the improvement of fuel economy. This paper introduces an energy management strategy for driving cycle identification. Twenty-two typical driving cycles are divided into five categories through Q-type clustering. Euclidean distance is used to identify the driving cycle. For each type of driving cycle, the energy management strategy parameters are optimized through genetic algorithms with fuel consumption and emissions as the goals. The results show that the EMS via driving cycle identification is more effective than a strategy that does not identify it. For comprehensive test cycles, the former's fuel consumption is optimized by 6%, SOC consumption is optimized by 1%, and there is a slight improvement in emissions.

1. Introduction

At present, pure electric vehicles are faced with some disadvantages, such as short driving range, inconvenient charge service, long charging time, short life and high battery pack prices. To solve these disadvantages, extended range electric vehicle (EREV) is designed with APU and small capacity battery pack [1]. EREV has the advantages of both the pure electric drive model and the hybrid power drive model, and it also can extend driving ranges and reduce cost. Thus, this model is gradually becoming a development trend of electric vehicle products [2]. Optimizing Energy management strategy (EMS) is an effective way to improve fuel consumption and emissions. Research shows that the uncertainty in vehicle driving cycles has an important impact on fuel consumption. EMS control parameters were adjusted in real time in a study [3] in which six representative standard cycles and 24 characteristic parameters were selected and used to identify comprehensive drive cycles. In another study [4], six urban conditions typical of China and the United States were selected as objectives of off-line optimization, and eight characteristic parameters including maximum vehicle speed were used to driving cycle identification [5].

In this paper, a variety of road conditions is considered, 22 typical driving cycles are selected as the standard mode library, and cluster analysis is conducted on them. The driving cycles are identified during the running of the vehicle, and then the control parameters are adjusted to minimize fuel consumption and emissions. The important control parameters are optimized offline by a genetic algorithm. Finally, the proposed vehicle EMS is simulated using driving cycle identification, and the results are analyzed.
in a MATLAB/Simulink environment.

2. Classification and identification of driving cycle

In this section, the EREV architecture is illustrated in figure 1. The parameter configuration of the whole vehicle is shown in table 1.

![Diagram of EREV system configuration](image)

**Figure 1.** System configuration of the EREV.

**Table 1.** Vehicle parameters.

| Name                      | Parameter |       |
|---------------------------|-----------|-------|
| Curing quality (kg)       | 6000      |       |
| FC max power (kw)         | 128       |       |
| Motor max power (kw)      | 105       |       |
| Generator max power (kw)  | 44        |       |
| Wheelbase (m)             | 3.36      |       |
| Wind resistance           | 0.44      |       |
| Windward area A (m²)      | 4.8       |       |
| Acceleration time (0-50km/h) (s) | 22 |       |
| Maximum grade             | 30%       |       |
| Pure electric range (km)  | 60        |       |

2.1. Classification of driving cycle

In this paper, the maximum speed of urban logistics vehicle is 90km/h is studied, so the driving cycles are selected from advisor as follows:

**Table 2.** Driving cycles.

| 1.1015 | 2.5PEAK | 3.ARTERLAL | 4.BUSRTE | 5.CBD14 | 6.COASt |
|--------|---------|------------|----------|---------|---------|
| 7.COMMUTER | 8.CONSTANT | 9.CSHVR | 10.ECE | 11.UDDS | 12.MANHATTAN |
| 13.NYCC | 14.NYCCOMP | 15.NYCTRUCK | 16.NYTC | 17.NewYorkBus | 18.SC03 |
| 19.STEP | 20.WVUCIFY | 21.FTP | 22.IM240 |

According to reference [6], 10 characteristic parameters are selected for identifying the driving cycles: time, distance, maximum speed, average speed, maximum acceleration, maximum deceleration, average acceleration, average deceleration, idle time, and number of stops.

To ensure the accuracy of classification, the 22 typical driving modes are divided into five categories according to the cluster analysis. In this paper, Q-type clustering is selected because it better suits the characteristics of the research objects. The distance is used to measure the similarity between different driving cycles. Euclidean distance [7] is used in this paper because it is the simplest and most accurate.

\[
\| y_i - y_j \| = \sqrt{\left( y_{i1} - y_{j1} \right)^2 + \cdots + \left( y_{im} - y_{jm} \right)^2} = \sqrt{\sum_{m=1}^{7} (y_{im} - y_{jm})^2}
\]

\( i \neq j \cap i,j \in Z^+ \cap i,j \in [1,22] \).

The classification results are shown in figure 2.

![Tree diagram for cluster analysis of driving cycles](image)

**Figure 2.** Tree diagram for cluster analysis of driving cycles.
2.2. Identification of driving cycle
To measure the similarity between driving cycles, a parameter is introduced to represent the progress [8]. If the five typical driving cycles in the library are the sample $A_n$ (n= 1–5), and the actual driving cycle sample is X, then the distance $\sigma(A_n, X)$ is defined as

$$\sigma(A_n, X) = 1 - \frac{1}{\sqrt{m}} \left( \sum_{k=1}^{m} (A_n(k) - X(k))^2 \right)^{1/2}$$

where m=10 is the number of characteristic parameters of the driving cycles, and k=1. The distance between $A_n$ and X is calculated according to the Euclidean formula

$$\sigma(A_i, X) = \max\{\sigma(A_1, X), \sigma(A_2, X), \ldots, \sigma(A_5, X)\}$$

The actual driving cycle X of the vehicle is considered to belong to the typical cycle sample $A_i$.

Five types of driving cycles in different cities, suburbs, and highways are randomly selected in this paper: The comprehensive test cycles (CYC_CBTRUCK+ CYC_CHTC_HT+ CYC_CWTVC+ CYC_WVUSUB+ CYC_MANHATTAN) are obtained and serve as the actual vehicle driving cycles. In order to ensure the accuracy of the drive cycle identification, select the smallest possible time interval to identify, a 200 s segment is selected to extract the parameter information of the standard driving cycle. The Euclidean distance is used to calculate the similarity to identify the drive cycles of each time period.

The driving cycle identification result is shown in figure 3.

![Figure 3. Speed-time curve of comprehensive driving cycle and result of driving cycle identification](image)

3. EREV energy management strategy optimizations
The rule-based energy management strategy is applied in this paper, as shown in Figure 4. where A is the minimum power output from the engine. In addition, limit the engine speed at 2000-3500r/min.

A genetic algorithm is a randomized search method that draws on the mechanisms of natural selection and genetics in biology. It does not have the same problem and has powerful global search ability, which is especially suitable for optimization in highly nonlinear complex systems. This method is more suitable for multi-objective optimization design of EREV. The basic optimization steps are in figure 5.
The system parameters selected for optimization are the allowed SOC upper limit \( H_i_{soc} \), allowed SOC lower limit \( L_i_{soc} \), maximum rate of increase of genset power \( M_{ax_{pwr rise rate}} \), and maximum rate of decrease of genset power \( M_{ax_{pwr fall rate}} \).

Genetic operations can be expressed as
\[
G_A = (C, J, P_0, M, \Phi, \Gamma, \Psi, T)
\]
where \( C \) is the individual coding method, \( J \) is the individual fitness function, \( P_0 \) is the initial population, \( M \) is the population size, \( \Phi \) is the genetic operator, \( \Gamma \) is the crossover operator, \( \Psi \) is the mutation operator, and \( T \) is the termination condition of the genetic operation.

The objective function is the fitness function defined as
\[
J(x) = F_c + E_c = \omega_1 \frac{F_c}{F_{cmax}} + \omega_2 \frac{E_{HC}}{E_{HCmax}} + \omega_3 \frac{E_{com}}{E_{comax}} + \omega_4 \frac{E_{NOx}}{E_{NOx_{max}}}
\]
where \( \omega_i \) (\( i = 1–4 \)) represents the weight of each optimization target, \( F_c \) is the cumulative value of each instantaneous fuel consumption \( F_c(t) \), \( E_c \) is the cumulative value of other pollutant emissions. The weight \( \omega_i \) is initially taken to be 0.25 to consider each sub-objective function in the optimization as being equally important. Taking the fitness function of equation (5), the optimized results are shown in table 3.

| Driving cycle category | \( H_i_{soc} \) | \( L_i_{soc} \) | \( M_{ax_{pwr rise rate}} \) | \( M_{ax_{pwr fall rate}} \) |
|------------------------|----------------|----------------|-----------------------------|-----------------------------|
| Category one           | 0.81           | 0.49           | 4920                        | -3120                       |
| Category two           | 0.77           | 0.43           | 5124                        | -2991                       |
| Category three          | 0.72           | 0.47           | 5207                        | -3080                       |
| Category four           | 0.79           | 0.40           | 4980                        | -3233                       |
| Category five           | 0.88           | 0.37           | 5119                        | -2895                       |

4. Results and discussion
The simulation model is built with the MATLAB/SIMULINK platform. The simulation analysis is carried out under the comprehensive test cycle (CYC_CBDTRUCK+ CYC_CHTC HT+ CYC_CWTVC+ CYC_WVUSUB+ CYC_MANHATTAN). The initial battery SOC is 0.7. During operation of the vehicle, the battery SOC is always changing in the charging and discharging high efficiency zone.
As seen in figure 6, the operating points of the engine are concentrated in the high-efficiency area. It can be seen from the graphs b and c that the engine operating point is on the optimal working curve, but the engine power distribution is different, and the optimized engine power distribution is more reasonable. The results for EMSs with and without cycle identification are shown in table 4 for comprehensive test driving cycles.

Table 4. Simulation results.

| Aims                  | No driving cycle identification | Driving cycle identification | improvement |
|-----------------------|---------------------------------|------------------------------|-------------|
| Fuel Consumption(L/100km) | 14.1                           | 13.25                        | 6%          |
| △SOC                 | 0.249                          | 0.246                        | 1%          |
| HC(g/km)             | 1.416                          | 1.410                        | 0.4%        |
| CO(g/km)             | 1.616                          | 1.602                        | 0.8%        |
| NOx(g/km)            | 0.660                          | 0.654                        | 0.9%        |

5. Conclusion

In this paper, an EMS based on the driving cycle identification has been proposed for power distribution of a hybrid power source. Cluster analysis is carried out on typical driving cycles, and the closeness of driving cycle is calculated to identify driving cycle. On this basis, the genetic algorithm is used to optimize the control parameters, which ultimately improves the economy and emission rate of the vehicle.

The main ideas and findings are:

1. Because of the randomness of hybrid vehicle driving cycles, driving cycles are identified to optimize the key parameters of vehicle control strategies. It is effective to optimize the fuel consumption and emissions of the EREV through the method of drive cycle identification.
2. The simulation and optimization results show that the fuel economy and emission performance of the vehicle are significantly improved by the proposed method. The fuel consumption is reduced by 6%, the battery consumption is improved by 1% and there is a slight improvement in emissions.

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