Adaptive Energy Management Strategy for Extended-Range Electric Vehicle Based on Micro-Trip Identification

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ABSTRACT In order to improve the fuel economy of an extended-range electric vehicle with the engine-generator, an adaptive energy management strategy has been proposed in this paper. First, micro-trip decomposition analysis of the standard driving cycles are conducted, and these micro trips are classified as four kinds of driving patterns by K-means clustering method. Second, an optimal energy allocation for the engine-generator and battery is designed by Pontryagin’s minimum principle (PMP). The proposed approach should realize the energy management and maintain the battery in a charge sustaining mode. Third, an online optimal control is conducted by a micro-trip identification algorithm. By utilizing the clustering driving patterns, the adaptive energy management strategy is achieved by the selection of optimal PMP co-state variable. Finally, the experimental performance comparisons for different control strategies and driving cycles are investigated to shown the efficiency of proposed controller.

INDEX TERMS Extended-range electric vehicle, micro-trip identification, adaptive energy management strategy, Pontryagin’s minimum principle.

I. INTRODUCTION

Nowadays, electric drive vehicle have been developed and applied widely to deal with the environmental concerns. However, due to the performance limitations of current batteries, battery electric vehicles driving in the long range and high speed still is a challenge. Extended-range electric vehicles (EREVs) with a hybrid energy source became an effective solution to improve the performance of pure battery driving vehicles [1], [2]. The engine of EREVs can be specially designed for power generation efficiency, which is different with that on the traditional fuel vehicle.

For the control of EREVs, an optimal energy allocation for the engine-generator and battery is the key issue that needs to be investigated. The driving force of EREV is from the electric motor, and the electric power is supported by the battery and engine-generator. The engine of EREV can work in the selected operating point according to the battery states and driving conditions. An efficient energy management strategy should satisfy the driving power demand while achieving different optimization targets, such as better fuel economy and battery lifespan.

To achieve optimal energy management for EREVs, a number of strategies have been developed which can be divided into two categories, i.e., rule-based and optimization-based. The rule-based strategy is the most direct and widely used method due to the advantages of stability, robustness and easy application [3], [4]. The control rules of operating modes and energy distribution often need to be designed by the experience with consideration for each component’s characteristics. To achieve better nonlinear optimization, fuzzy logic control strategies are employed by adding the fuzzification process based on the experience or neural network training [5]. These rule-based strategies depending on the prior experience have the disadvantages of poor adaptivity when faced with complex road conditions [6], [7].

Optimization-based energy management is designed by an equivalent consumption minimization strategy [8]. A number of optimization algorithms such as dynamic programming (DP), quadratic programming (QP) and Pontryagin's
minimum priciple (PMP) [9]–[11], have been widely applied to develop various energy management solutions. DP-based approach is effective to find a global optimal solution for a deterministic problem, which limited for online energy management applications. PMP-based approach is a typical equivalent consumption minimization strategy. The challenge of this approach is the design of equivalent factor, which is the co-state variable of PMP algorithm. The co-state variable should be optimized according to the driving conditions and the battery parameters [12].

Most previous literatures have investigated control strategies for parallel hybrid electric vehicle, and find an optimal torque allocation for the engine and motor [18]–[20]. For an extended-range electric vehicle with the engine-generator, the online optimization of engine operating mode with battery charge sustaining strategy has not been solved effectively. How to achieve an adaptive energy management in unknown driving cycles is the main challenge for the real-time application. To solve the discussed problems on EREVs, this paper proposes an adaptive energy management strategy through the establishment of a multi-micro-trip optimization database. The main target is to improve the fuel economy and maintain the battery SOC around the stable charge sustaining mode. For each micro-trip, the optimization process are conducted by the PMP-based approach to find related co-state variables. The real driving cycles can be classified as specific driving patterns by the use of micro-trip correlation analysis. For the online application, the co-state variable of controller is adaptively adjusted to have the optimal energy efficiency with respect to different driving conditions. The proposed online energy management strategy has been verified by the experimental comparison with DP-based global optimization method.

The paper is organized as follows. Section II gives a brief review of an EREV dynamic model and its parameters. Section III presents the establishment of micro-trip samples and the related clustering method by K-means algorithm. Section IV describes the design of PMP-based adaptive energy management strategy, including micro-trip identification and co-state variables modification. Section V offers a detailed description of the experimental verification for proposed control strategy design in the combined driving cycles. The conclusion of the EREV energy management strategy in this paper is summarized in Session VI.

II. SYSTEM MODELING

The basic structure and energy flow of the EREVs are shown in Figure 1. The electricity power of the EREV is composed by two parts: the power battery and assistance power unit (APU). The engine-generator system is connected to the electric power bus, and can work together with the power battery. Based on the driver’s command, the desired electric power is allocated between the engine-generator and battery. The APU consists of a 1.5 L gasoline engine and a 50 kW permanent magnet generator. The target vehicle is a sport utility vehicle (SUV) and the main vehicle parameters are listed in Table 1.

### TABLE 1. Main vehicle parameters.

| Parameters                  | Value          |
|-----------------------------|----------------|
| Vehicle mass                | 1440 kg        |
| Reduction ratio             | 7.55           |
| Wheel radius                | 0.315 m        |
| Air resistance coefficient  | 0.345          |
| Wind resistance area        | 2.36 m²        |
| Roll resistance coefficient | 0.012          |
| Transmission efficiency     | 0.9            |
| Engine type                 | 1.5L gasoline engine |
| Generator power             | 50 kW          |
| Drive motor power           | 60 kW          |

A. ARCHITECTURE OF EXTENDED-RANGE ELECTRIC SYSTEM

In order to evaluate the power management strategy of EREVs, a forward vehicle model based on the energy flow of powertrain system is established. The output torque of the drive motor needs to overcome the road loads. These loads include rolling resistance, aerodynamic resistance, ramp resistance and acceleration resistance, which can be reflected in the vehicle driving equation:

\[
P_m = P_{bat} + P_{APU} \tag{1}
\]

\[
P_m = \frac{u}{\eta} \left( m g \mu_f \cos \alpha + \frac{1}{2} C_D A_D \rho u^2 + m g \sin \alpha + \delta m \frac{du}{dt} \right) \tag{2}
\]
where $P_m$ is the demanded power of the driving motor; $P_{bat}$ is the power of the battery, which can be positive or negative value; $P_{APU}$ is the output power of engine-generator system. $\eta$ is transmission efficiency; $m$ is vehicle reference mass, $g$ is acceleration of gravity; $\mu_f$ is rolling resistance coefficient; $\alpha$ is slope angle; $C_D$ is wind resistance coefficient; $A_D$ is windward area; $\rho$ is air density; $u$ is vehicle speed; $\delta$ is vehicle equivalent inertia coefficient.

### B. APU MODEL

Since there is no mechanical transmission between the engine and driving wheels, the engine can be controlled to choose the optimal operating point without the limitation from vehicular speed. In order to obtain a low fuel consumption rate in the different output power levels, the optimal efficiency curve of APU needs to be found. Here an experimental data fitting method is employed as the modeling of APU engine and generator, which can reduce the computational burden without much influence on the control precision. For any specified APU power $P_{APU}^*$, the corresponding minimum fuel consumption rate $b_{APU}^*$ can be calculated by using the performance characteristics maps of engine and generator:

\[
b_{APU}^* = \min_{\eta_e(T_e, n_e)} \frac{b_e(T_e, n_e)}{\eta_e(T_e, n_e)} \tag{3a}
\]

\[
s.t. \quad \frac{T_e \cdot n_e}{9550} \cdot \eta_g(T_g, n_g) = P_{APU}^* \tag{3b}
\]

\[
0 \leq n_e \leq n_{\max} \quad 0 \leq T_e \leq T_{\max}(n_e) \tag{3c}
\]

where $b_{APU}^*$ is the optimal fuel consumption rate of APU when the demanded power is $P_{APU}^*$. $b_e$ is the engine fuel consumption rate. $T_e$ and $T_g$ are engine torque and generator torque. $n_e$ and $n_g$ are engine speed and generator speed. $\eta_e$ is the generating efficiency of generator. $n_{\max}$ is the maximum speed of APU. $T_{\max}$ is the smaller value from the external characteristics curve of engine and generator. Fig. 2 shows the fuel consumption rate map of APU. The blue curve is the minimum fuel consumption rate with respect to different APU speed.

### C. BATTERY MODEL

The energy storage battery of the EREVs is designed by using the Rint model [13]. The Rint model treats the battery as an equivalent circuit consisting of a voltage source and a resistor in series. This kind of battery model can support enough precision but low computational complexity. According to Kirchhoff’s voltage law, the power of battery can be expressed by

\[
P_b = (E_b \times I_b) - I_b^2R_b \tag{4}
\]

where $P_b$ is the output power of power battery, $I_b$ is the output current of power battery, $E_b$ is the electromotive force of power battery, $R_b$ is the internal resistance of power battery.

Then, the current of the energy storage battery can be expressed by

\[
I_b = \frac{E_b - \sqrt{E_b^2 - 4000R_bP_b}}{2R_b} \tag{5}
\]

and the charged state of the energy storage battery $SOC$ is

\[
SOC(t) = \frac{I_b(t)}{3600Q_b} \tag{6}
\]

where $Q_b$ is the capacity of power battery.

### III. DECOMPOSITION OF DRIVING CYCLES

The traditional energy management approaches tend to use the existing driving cycles to develop a global control strategies [14]–[16]. Since the real driving cycle are changed dynamically, an adaptive energy management approach via micro trip recognition and PMP-based optimization is proposed to improve the energy efficiency of EREVs. To achieve the optimal result in unknown driving cycles, the micro trip recognition method has been designed to classify the typical driving patterns.

#### A. ESTABLISHMENT OF MICRO TRIPS

The samples of micro trips in the adaptive control strategy are supposed to be typical and representative. This study employed ten standard driving cycles from different driving condition and countries as the sample drive cycles [21], [22]. These standard driving cycles are shows in Table 2, which can cover the common speed range and acceleration range of the vehicles. The micro trips are established by the decomposition of these cycles. Each micro trip is selected to have complete start-stop process, and has different driving characteristics with other micro trips. Moreover, if the time window of micro trip is too short, the error of the driving pattern
recognition will be increased. Based on these analysis, for each micro trip $M_i$, the corresponding sample $Y_i$ is obtained by the following methods:

- If the time length of micro trip $M_i$ is not less than 150 seconds, then micro trip $M_i$ is directly taken as the sample $Y_i$.
- If the time length of micro trip $M_i$ is less than 150 seconds, a sample $Y_i$ is generated by multi-duplicated micro trips until the total time length is more than 150 seconds.

The sample parameter matrix $A$ can be standardized with zero mean value. Thus the parameter vector of the characteristic parameter $a_{ik}$ can be rewritten as $b_{ik}$, which is calculated by

$$b_{ik} = \frac{a_{ik} - \mu_k}{\sigma_k}$$

where $\mu_k$ is the sample mean of characteristic parameter $C_k$, and $\sigma_k$ is the sample standard deviation of characteristic parameter $C_k$. These values can be calculated by

$$\mu_k = \frac{1}{11} \sum_{i=1}^{11} a_{ik}$$

$$\sigma_k = \frac{1}{10} \sum_{i=1}^{11} (a_{ik} - \mu_k)^2$$

Since a large number of characteristics parameters will lead to a complex algorithm and a reduced identification efficiency, a correlation analysis of the selected characteristic parameters to the fuel economy is conducted. According to the statistics theory, the pearson correlation coefficient $\rho_k$...
between the characteristic parameter $C_k$ and the fuel consumption $r$ can be calculated by

$$\rho = \rho(b_{ik}, r) = \frac{\text{Cov}(b_{ik}, r)}{\sqrt{D(b_{ik})} \sqrt{D(r)}}$$  \hspace{1cm} (11)$$

Based on the Equ. (12), the pearson correlation coefficient between two different characteristic parameters can also be calculated and denoted by $\theta_{ik}$. The correlation results of eleven driving characteristic parameters in Table 3 can be found in appendix. In order to reduce the computational complexity while retaining the essential driving information, the dimensions of characteristic parameters should be decreased. The effective feature parameter set $\Omega(r)$ is selected according to the following rules:

- All effective feature parameters in $\Omega(r)$ should have $|\rho_{ik}| > 0.2$. It means that the absolute value of correlation between $C_k$ and $r$ should be larger than 0.2.
- All effective feature parameters in $\Omega(r)$ should have $|\theta_{ik}| < 0.8$. It means that if the absolute value of correlation between two characteristic parameters is larger than 0.8, there is only one characteristic parameter can be reserved.

The final selected characteristic parameters for the relative correlation parameter are average speed, maximum acceleration and ratio of idling time. These parameters can be used to represent the features of different micro trips with reduced computation. The effective feature parameter set $\Omega(r)$ is expressed as

$$\Omega(r) = \{C_2, C_4, C_{10}\}$$  \hspace{1cm} (12)$$

**C. CLASSIFICATION OF MICRO TRIPS**

In order to classify the micro trips from the standard driving cycles, a modified K-means algorithm is employed for the clustering method. From the sample database, one micro trip is selected as an initial clustering center $c_1$. Then the distances $D(i)$ between other samples $Y_i$ and the current clustering center can be calculated. Each sample has a probability $P(i)$ to be selected as the next clustering center $c_k$. The decision of new clustering center is decided by the cumulative probability. The calculation of probability $P(i)$ and clustering center $c_k$ can be expressed by

$$P(i) = \frac{D(i)^2}{\sum_{i=1}^{n} D(i)^2}$$  \hspace{1cm} (13)$$

$$\text{Cluster}(c_k) = \{i \mid \sum_{x=1}^{i-1} P(x) \leq r \leq \sum_{x=1}^{i} P(x)\}, \quad 0 \leq r \leq 1$$  \hspace{1cm} (14)$$

where $n$ is the size of samples, $D(i)$ is the distances between the $i-th$ sample and the clustering center, $\sum_{x=1}^{i} P(x)$ is the cumulative probability of the $i-th$ sample.

Based on the above results, the Euclidean distance of each micro-trip sample to the clustering centers can be achieved. By the calculating of the sample means, the average value of each cluster can be set as the clustering center. The algorithm repeats the previous steps until the clustering center of every sample cluster has no change. In order to reduce the influence from the different dimensional of parameters, the characteristic parameters of driving cycle should be normalized. Here a Min-Max normalization method is employed to take linear transformation of characteristic parameters.

Based on the principal component of micro-trip samples, the three dimensional scatter plot of K-means clustering results is shown in Fig. 5. It can be found that all samples are classified as four clusters. Class-1 shown a city driving congestion condition, which has low speed and acceleration, but long time ratio of idle speed. Class-2 with relative reduced time ratio of idle speed is normal city driving condition. Class-3 with relative high average vehicle speed and acceleration is suburban driving condition. Class-4 shown a high speed driving condition which has largest vehicle speed and acceleration, but smallest time ratio of idle speed. The final clustering results for driving cycles are shown in Table 4.

![Figure 5. Three dimensional scatter plot of K-means clustering results.](image)

**TABLE 4. Clustering results for driving cycles.**

| Clustering results | Average speed | Time ratio of idle speed | Maximum acceleration |
|--------------------|---------------|--------------------------|----------------------|
| Class-1            | 2.128 m/s     | 69.12%                   | 0.883 m/s²           |
| Class-2            | 3.870 m/s     | 20.18%                   | 1.023 m/s²           |
| Class-3            | 8.389 m/s     | 18.89%                   | 1.513 m/s²           |
| Class-4            | 17.630 m/s    | 11.55%                   | 2.409 m/s²           |

By using the clustering results, four kinds of driving cycles are synthesized to show the different driving conditions. The micro-trip samples with closest distance to relative clustering center can be considered into the synthetic driving cycles. Since the duration of driving cycles are generally taken from 600s to 1800s, here four driving cycles are constructed with 1200s. Fig. 6 shows the classification results of different micro-trip samples. These four driving cycles are designed for the online driving pattern recognition and related strategy optimization.
According to Eqn. (15) and Eqn. (17), Hamiltonian function of PMP algorithm can be established as:

\[ H(SOC(t), P_{APU}(t), \lambda(t)) = \dot{m}_f(P_{APU}(t)) + \lambda(t)f(SOC(t), P_{APU}(t)) \]  

where \( \lambda(t) \) is the co-state variable. Then the differential of co-state variable \( \lambda(t) \) can be wrote as

\[ \dot{\lambda(t)} = -\lambda(t) \frac{\partial f}{\partial (SOC)} \approx 0 \]  

Since the battery of EREVs is supposed to work in charge-sustaining (CS) model, the SOC of battery \( SOC(t) \) is approximately constant. Therefore, \( \dot{\lambda(t)} \) can be approximatively regarded as a constant value. The optimal control of the allocated APU power at time \( t \) is:

\[
P^*_{APU}(t) = \arg \min P_{APU}(t), \lambda \quad H(P_{APU}(t), \lambda)
\]

\[
= \dot{m}_f(P_{APU}(t)) - \lambda \frac{I_0(t)}{3600Q_b}
\]

\[ s.t. \quad SOC(t_0) = SOC_0 \]

\[ SOC(t_f) = SOC_f \]

where \( SOC_0 \) is the lower limiting value, and \( SOC_f \) is the upper limiting value. The initial value of co-state variable can be obtained by shooting method [17]. Based on the above PMP-based control strategy, the optimal co-state variable for the four driving cycles from the clustering results can be achieved.

**B. MICRO-TRIP IDENTIFICATION**

During the online application of energy management control, it set time \( t = 0 \) at the beginning of each micro-trip. The system records the driving information per second after the start of vehicle. For each micro-trip within a maximum of 150s, the vehicle driving information is saved in the database \( X(t) \), which is expressed as equation (21).

\[
X(t) = \begin{cases} 
  [x(1), \ldots, x(t)] & t < 150 \\
  [x(t - 149), \ldots, x(t)] & t \geq 150 
\end{cases}
\]

Based on the algorithm of K-means method, the distance discrimination method is applied to represent the correlation between the real micro-trip and clustering driving cycles. Here the Euclid closeness is employed as the evaluation criteria for classification. The Euclid closeness is calculated by

\[
\sigma(A_n, X) = 1 - \frac{1}{\sqrt{m}} \left( \sum_{i=1}^{m} (A_n(i) - X(i))^2 \right)^{\frac{1}{2}}
\]

where \( A_n \) is the clustering center of four classified driving cycles, and \( n = 1, 2, 3, 4 \). \( m \) is the number of characteristic parameters, including average vehicle speed, time ratio of idle speed and maximum acceleration. \( X \) is the recorded data of real driving cycle. The Euclid closeness of the classified driving cycle with largest value is selected as the identified result of driving condition:

\[
\sigma(A_n, X) = \max \{ \sigma(A_1, X), \sigma(A_2, X), \sigma(A_3, X), \sigma(A_4, X) \}
\]
C. CO-STATE VARIABLES MODIFICATION

For the energy management strategy of the EREVs, the charge-sustaining (CS) model is the most important condition to impact on the fuel economy. It is necessary to ensure that the battery SOC fluctuates within a certain range to prevent the battery overcharge or overdischarge. Since these is error between the actual driving condition and the identified sample $Y_i^*$, the error accumulation can make the battery SOC deviate from the expected range. To achieve charge sustaining mode of vehicle battery, the co-state variable of PMP algorithm should be modified with the consideration of battery SOC. The control strategy framework is shown in the Fig. 7.

\[ \lambda(t) = \lambda_n + k_p \Delta SOC(t) + k_i \int \Delta SOC(t) dt \]

(24)

where $\lambda_n$ is the optimal co-state variable for identified driving pattern, $k_p$ and $k_i$ is the proportionality coefficient and integration coefficient. $SOC_{tar}$ is the target SOC of the charge sustaining mode.

Here the target SOC of the charge sustaining mode is set as 0.55. To simplify the control strategy, a boundary of co-state variable is designed by the SOC range, which is expressed as

\[ \lambda^*(t) = \begin{cases} 
\lambda_{on} & \text{SOC}(t) < 0.53 \\
\lambda_{off} & \text{SOC}(t) > 0.57 \\
\lambda(t) & \text{else} 
\end{cases} \]

(25)

where $\lambda_{on}$ is the co-state variable that makes APU turn on, and $\lambda_{on}$ is set as $-3700$; $\lambda_{off}$ is the co-state variable that makes APU turn off, and $\lambda_{off}$ is set as $-3400$.

By taking the NEDC driving cycle as the example, the changed battery SOC curves with different initial SOC are shown in Fig. 8. It can be found that the SOC of battery is controlled in a stable range by the co-state variables modification.

V. VERIFICATION AND DISCUSSION

In order to verify the performance of the proposed adaptive energy management strategy, simulations were carried out under the different driving cycles. Here two kinds of driving cycles were applied for the simulation verification: WLTC driving cycle and Nuremberg R36 driving cycle. Nuremberg R36 driving cycle is not used as the sample in the above clustering analysis, and can be used to verify the control effect in the unknown driving condition. The simulations are conducted in a combination of three driving cycles. Corresponding speed profiles of these two driving cycles, the combined driving cycles are shown in Fig. 9 and Fig. 10. By the micro-trip identification, the driving pattern recognition for the combined driving cycles are also shown in Fig. 9 and Fig. 10. It can be found that the index of clustering results can well match the driving condition to the classified four driving patterns.

During the online application, the fuel consumption and the battery SOC are two indicators to evaluate the performances of the proposed strategy. Table 5 shows the performance
comparison of different control strategies and driving cycles. Here DP-based global optimization for the control strategy is applied as the reference of ideal result. Moreover, traditional rule-based control strategy is employed to show the comparative results with the proposed adaptive energy management strategy. Rule-based algorithm and DP-based algorithm were built based on the previous literatures respectively [7], [9].

FC is the fuel consumption per hundred kilometers from the results of combined driving cycles. SOC express the end-state of battery SOC after the simulations. The SOC variation curves in comparison with other control algorithms are shown in Fig. 11 and Fig. 12.

It can be observed that the DP-based strategy and proposed control strategy can maintain the ending SOC in the vicinity of the setting value, while the rule-based control strategy may lead to obvious drift of ending SOC. Due to the self-adaptive adjustment of PMP co-state variable by the battery SOC, the proposed adaptive strategy has a smallest SOC fluctuation than others. From the Fig. 11, the DP-based globally optimization has a larger SOC fluctuation which makes against the healthy lifespan of vehicle batteries. By comparing the results of fuel consumption, the DP-based globally optimization in the case of knowing the driving cycle data in advance has the best performance. The proposed control strategy with online driving pattern recognition can achieve similar performance as the DP-based method, and has more fuel savings than the rule-based control strategy. The adaptive energy management control strategy can dynamically regulate the co-state variable of PMP algorithm according to the driving condition, and it can achieve optimized fuel economy under completely unknown driving cycles.

The simulated results of APU output power under different combined driving cycles are shown in Fig. 13 and Fig. 14. Since the Nuremberg R36 cycles is a kind of urban road driving condition, the output power of the APU is smaller than the WLTC cycles. From the comparative results of WLTC cycles, the number of APU starts can be reduced by the proposed control. This is because the DP-based method is a global optimization without the consideration of
TABLE 6. Correlation coefficient between the characteristic parameters and fuel consumption.

| Correlation | C_1 | C_2 | C_3 | C_4 | C_5 | C_6 | C_7 | C_8 | C_9 | C_10 | C_11 |
|------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|------|------|
| Fuel consumption | -0.63 | -0.69 | -0.51 | -0.61 | 0.138 | -0.257 | 0.00 | 0.553 | -0.05 | 0.385 | 0.385 |

TABLE 7. Correlation coefficient among the characteristic parameters.

| Correlation | C_1 | C_2 | C_3 | C_4 | C_5 | C_6 | C_7 | C_8 | C_9 | C_10 | C_11 |
|------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|------|------|
| C_1       | 1   | 0.977 | 0.952 | 0.531 | -0.681 | 0.056 | -0.344 | 0.294 | 0.497 | -0.483 | 0.483 |
| C_2       | 0.977 | 1   | 0.927 | 0.536 | -0.653 | -0.046 | -0.305 | 0.303 | 0.473 | -0.446 | 0.446 |
| C_3       | 0.952 | 0.927 | 1   | 0.517 | -0.674 | 0.109 | -0.424 | 0.315 | 0.532 | -0.436 | 0.436 |
| C_4       | 0.531 | 0.536 | 0.517 | 1   | -0.703 | 0.676 | -0.537 | 0.803 | 0.646 | -0.173 | 0.173 |
| C_5       | -0.681 | -0.653 | -0.674 | -0.703 | 1   | -0.412 | 0.684 | -0.431 | -0.879 | 0.321 | -0.321 |
| C_6       | 0.056 | -0.046 | 0.109 | 0.676 | -0.412 | 1   | -0.611 | 0.573 | -0.548 | 0.133 | -0.133 |
| C_7       | -0.344 | -0.305 | -0.424 | -0.537 | 0.684 | -0.611 | 1   | -0.366 | -0.744 | 0.092 | -0.092 |
| C_8       | 0.294 | 0.303 | 0.310 | 0.803 | -0.431 | 0.573 | -0.366 | 1   | 0.376 | -0.061 | 0.061 |
| C_9       | 0.497 | 0.473 | 0.532 | 0.646 | -0.879 | -0.548 | -0.744 | 0.376 | 1   | -0.265 | 0.265 |
| C_10      | -0.482 | -0.446 | -0.436 | -0.173 | 0.321 | 0.133 | 0.092 | -0.061 | -0.265 | 1   | -1 |
| C_11      | 0.482 | 0.446 | 0.436 | 0.173 | -0.321 | -0.133 | -0.092 | 0.061 | 0.265 | -1   | 1 |

FIGURE 14. Output power of APU system under combined Nuremberg R36 cycles.

transient behaviour. The proposed adaptive approach can dynamically update the co-state variable and guarantee that the battery SOC maintains near the initial setting value. This kind of characteristic can improve the noise vibration and harshness (NVH) of powertrain system, which is useful for the driving comfort.

VI. CONCLUSION

This paper is devoted to the online energy management strategy of extended-range electric vehicles. The relationship between the optimal co-variable variables of PMP control and the characteristic parameters of driving conditions have been analyzed. The micro-trip identification method was employed to realize optimization of the co-state variable of PMP algorithm under unknown driving cycles. Moreover, to achieve a charge sustaining mode of battery, the real-time co-state variable modification with a pair of boundary is designed according to the energy balance function and battery status. Simulation results are compared with the global optimization method, and the improved fuel economy manifests the effectiveness and adaptivity of the proposed online control strategy.

The real-time driving conditions are classified into four kinds of driving cycles from the clustering results in this paper. In future study, more classifications to express complex driving cycles will be considered. In addition, the hardware-in-the-loop experimental study on the EREVs will also be conducted based on the proposed algorithm.

APPENDIX

Based on the correlation analysis in the section III part B, the pearson correlation coefficients between the characteristic parameters and the fuel consumption are shown in Table 6, and the pearson correlation coefficients between two different characteristic parameters are shown in Table 7.

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