A Control Strategy of Range Extended Electric Vehicles Based on Driving Condition Identification and Pontryagin’s Minimum Principle

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Abstract — Range extended electric vehicles (REEVs) provide potential to increase driving mileage and lower the fuel consumption compared with common hybrid electric vehicles (HEVs). To distribute the power between the auxiliary power unit (APU) and the energy buffer (normally is a battery) without sacrificing fuel economy, many optimal control strategies have been proposed. Some strategies, however, seldom take the driving condition into account which could influence the consequence significantly of the optimal control strategies. Thus, this paper firstly evaluates the statistical feature of typical driving cycle with novel method, then by applying the learning vector quantization (LVQ) network, the real-time driving condition can be determined. According to specific driving condition, the Pontryagin’s minimum principle (PMP) as a global optimal solution is used to distribute the power. Simulation study proves the proposed control strategies should be a possible solution with reasonable viability.

Keywords — optimal control; range-extended electric vehicle; learning vector quantization network; Pontryagin's minimum principle; driving condition identifying

I. INTRODUCTION

Range extended electric vehicles (REEV) can be a potential new means of transportation which synthesizes the merit of pure electric vehicles (EVs) and serial hybrid electric vehicles (SHEVs). The REEVs, compared with the EVs and SHEVs, have a more reasonable fuel economy and driving mileage [1]-[4]. The research and development of REEV has pay much attention from researchers with the aim to provide solution to protect environment and natural resource. Schematic diagram of EREV is shown in Fig. 1, an Internal Combustion Engine (ICE) is connected to a generator by an axis. The APU is connected to the drive motor and battery pack via an electrical power bus, and usually, via some kind of coupling device with varying degrees of complexity.

Figure 1. Schematic diagram of a typical REEV

In the process REEVs research and development, there are quite a number of challenge issues. To be specific, the control strategy is one of the key problems[5]-[27]. The problem can be concluded as follows:

- a. How to fulfill the driver’s tractive demand with ideal fuel economy.
- b. How to keep the battery state of charge (SOC) fluctuation when REEV switches into change sustaining (CS) stage in a rational range while ensure REEV can follow the driving requirement in different driving condition.

To tackle the issue, massive work has been performed in past 20 years by researchers. Among the massive research, three types control method are favored: the control strategy based on heuristic knowledge, i.e. rule based control, fuzzy logic control, the control strategy based on numerical optimization, i.e. dynamic programming (DP), the control strategy based on analytical optimization, i.e. the Pontryagin’s minimum principle (PMP) [5]-[27]. To the control strategy based on heuristic knowledge, some rule based control strategies have been proposed in [5]-[7]. Also, several fuzzy-logic control strategies are adopted in [8]-[10]. The control strategy based on heuristic knowledge is relatively simple and easy to be applied in real-time. However they mainly based on the expert experience which means they cannot robust against the driving condition change. To the control strategies based on numerical optimization, some optimal control theory like DP has been come up with in [11]-[14]. Although the optimal control theory like DP provide global optimization, they require aforementioned information about the driving cycle which means they cannot be applied in real-time environment directly. To the control strategies based on analytical optimization, some researchers chose the PMP theory to perform the control with reasonable calculation and hypothesis [15]-[20]. The PMP, nevertheless, is also a global optimal solution which the effect is affected by the driving cycle largely. Moreover, researchers tend to apply mathematic methods in designing control strategy [21]-[25],
these method cannot make sure the control strategy adapt to the change of driving condition. From the review of current research status about the REEV control strategy, some researchers tended to eliminate the unfavorable influence of driving condition by taking the characteristic features of drive cycle into account when designing the control strategy for REEV. In [26]-[32], the driving condition is appropriate considered by investigating the characteristic features of different driving cycle through the statistic method. Then the vehicle control unit (VCU) identifies the driving condition using the characteristic features of different driving cycle and performs corresponding control with optimal control theory in the specific driving condition. How to identify the driving condition is the key step to perform control. This paper proposes the advance intelligent control strategy (AICS) employing a driving condition identifier by studying novel designed characteristic features of different driving cycle. The driving cycle information is incorporated into the optimal control achieved by PMP, providing the enhanced performance of REEV in different driving condition. Through the simulation, it is proved that the proposed AICS improves the performance of REEV.

The remainder of the paper is organized as follows. Next section deals with the static model of the REEV. In section 3, the driving condition identifying process is discussed. In section 4, the optimal control based on PMP in specific driving condition is shown. At last, the effectiveness of the proposed AICS is proved through the simulation in Matlab/Simulink.

II. STATIC MODEL OF THE REEV

When the vehicle is operating, if it is treated as a mass-point, the vehicle dynamic equation can be written as:

\[ M_{veh} \frac{dv}{dt} = F_{trac} - F_{roll} - F_{aero} - F_{grade} \]  

where \( M_{veh} \) is vehicle mass, \( V_{veh} \) is vehicle velocity, \( F_{trac} \) is tractive force at the driving wheels, \( F_{roll} \) is rolling resistance, \( F_{aero} \) is the aerodynamic resistance, and \( F_{grade} \) is gradient resistance. The equation of the rolling resistance, aerodynamic resistance, gradient resistance, can be expressed as:

\[ F_{roll} = \mu M_{veh} g \cos \alpha \]  

\[ F_{aero} = \frac{1}{2} C_d A_f V_{veh}^2 \]  

\[ F_{grade} = M_{veh} g \sin \alpha \]  

where \( g \) is the local gravitational acceleration value, \( \alpha \) is the road slope angle, \( \mu \) is the rolling resistance coefficient, \( C_d \) is the aerodynamic drag coefficient, \( A_f \) is the vehicle frontal area.

Batteries are non-linear systems whose main variables include state of charge (SOC), voltage, current, temperature, etc. In our simulation, SOC is regarded as the main parameter to show the state of the battery. The state of charge can be written as:

\[ SOC(t) = \frac{\int_{t_0}^{t} i(U) dt}{Q_{batt}} \]  

where \( \int_{t_0}^{t} i(U) dt \) is the amount of charge left/entered the battery pack (the current-time integral) due to driving energy requirements, braking energy recovery, and engine-generator power generation. \( Q_{batt} \) is the total amount of charge the battery can hold within its operating range. The battery voltage can be expressed as:

\[ v_{bat} = v_{oc} (SOC) + v_{int} (U) \]  

where \( v_{oc} \) is the open circuit voltage, \( v_{int} \) is the voltage drop caused by Ohmic losses.

The engine power can be calculated by the following equation:

\[ P_e = \frac{V_{batt}}{t_{on}} (M_{veh} g \cos \alpha + \frac{gV_{veh}^2}{2} + M_{veh} g \sin \alpha) \]  

where \( P_e \) is the engine power, \( \eta \) is the transmission system efficiency.

The fuel consumption of the engine can be represented as:

\[ q_f = \frac{b_e}{\eta_{e}} \]  

where \( q_f \) is fuel consumption of engine, \( b_e \) is brake specific fuel consumption (BSFC), and \( \eta_{e} \) is working time. The relationship between \( b_e \) and engine efficiency \( \eta_{e} \) can be represented as:

\[ b_e = \frac{3600000}{(SFC)R} = \frac{k}{\eta_{e}} \]  

where \( k = 3600000/R, R = 4600 \text{ kJ/kg} \) (caloric value of gasoline). Fuel consumption of the engine can be solved by the following equation:

\[ q_f = \frac{kR t}{\eta_{e} \eta_{g}} \]  

The optimization algorithm used in this paper evaluates the efficiency of the engine and generator. Numerical models of the engine and generator efficiencies were established by experiment. Experiment results of the engine efficiency under different engine speed and torque is shown in Figure 2.

![Figure 2. Numerical model of engine efficiency](image)

Experiment results of generator efficiency under different input speeds and torque is obtained by experiment and shown in Figure 3.

![Figure 3. Numerical model of generator efficiency](image)
III. DRIVING CONDITION IDENTIFICATION PROCESS

Based on the standard driving cycle data to train driving condition identifier, then the real-time driving condition is determined. In this process, the precise of the driving condition identifier is of the vital importance. To train an accurate driving condition identifier, two key point need to tackle.

a. Choosing appropriate history data (i.e. reasonable standard driving cycles) for training.

b. Choosing suitable characteristic value which can reflect the specific driving condition.

When choosing the appropriate history data, some researchers have given their options. In [33], Sierra Research Inc. has defined 11 driving cycles that reflect the driving condition of passenger car and light duty vehicle in urban areas, i.e. LOS A-F. However, these designed driving cycles partially tend to U.S. driving conditions, without ideal adapt to driving conditions in other place. In [28] Ericsson proposed 62 characteristic parameters to identify the driving condition by investigating given driving cycles. Theses giver driving cycles are based on the research in Sweden, thus might not be suitable for Asian driving conditions. Based on the literature review, this paper study the standard driving cycles in different region around the world, then extracts characteristic parameters from these standard driving cycles. The driving condition can be classified into three types: the traffic jam, the urban drive, the highway drive. The traffic jam type mainly represents vehicles driving in the downtown where the traffic situation is poor that require vehicles start and stop frequently. The vehicle speed in traffic jam type is very low. The urban drive type mainly represents vehicles driving in the city arterial road. In this type, the vehicle speed is normal although there are some crossroads. The highway drive type mainly reflect vehicle driving in the road like highway with a relatively high speed. In Europe, Asia, U.S., government or organization all formulate their standard driving cycles, i.e. NEDC, JC08, UDDS. After study, the following driving cycles in Table 1 are chosen to extract the characteristic parameters.

<table>
<thead>
<tr>
<th>Driving condition type</th>
<th>Chosen driving cycle</th>
</tr>
</thead>
<tbody>
<tr>
<td>Traffic jam</td>
<td>Artemis_Urban</td>
</tr>
<tr>
<td>Urban drive</td>
<td>UDC</td>
</tr>
<tr>
<td>Highway drive</td>
<td>UDDS, EUDC, HWFET</td>
</tr>
</tbody>
</table>

The speed curve of chosen driving cycles are shown as follows:

When choosing the characteristic parameters, Ericsson use 62 parameters [28], Jong Sob prefer 40 [34]. There is no rules to follow when choosing the characteristic parameters. In this study, 22 parameters are chosen. When calculate the characteristic parameters values, former researchers divided the driving cycles into a few segments based on equal time interval or distance interval. These methods may easy to perform, but the data matrix can be small which can lead the driving condition identifier less accurate. In this study, the driving cycles are divided into small segments combined with time interval method and distance interval method that is illustrated in Fig. 5. Compared the former research [27]-[34], the time interval is one-eighths of total operating time, while the distance interval is one-sixth of the total distance. As the discussed, when training the LVQ network, the training data acquired form consists of a [22*6] matrix. In each training matrix. There are also 16 training sub-matrix. In this way, the data used to train LVQ network can be relatively large which is favored in training. The LVQ network is an effective tools to classify the target class [34]. Normally, an LVQ network consists of the input layer, the hidden layer (also is called the competitive layer), and the output layer (also is called the linear layer). The schematic of the LVQ network can be seen in Figure 6.
The classify process inside the LVQ network mainly includes two stages. Firstly, a certain number of vectors are input and the hidden layer identifies the input vectors. Secondly, the output layer output the target classes. The identification process in hidden layer can be shown as follows. Neurons (represented by E) in the hidden layer evaluate the Euclidean distance between the input vector $a$, and the possible subclass vector $p$. At last, the closest subclass to the input vector is valuated 1, other subclasses are 0. The result of driving condition identification by the LVQ network can be seed in Table II.

In the table, there are some incorrect identifications. These false identifications may be the result of segment similarities between certain driving cycles.

IV. THE POWER DISTRIBUTION CONTROL (PDC) STRATEGY

To the REEV, its battery capacity is larger than common hybrid vehicle. Hence, acquiring energy from battery is favored in charge depleting (CD stage) for the benefit to fuel economy. In this study, the REEV in CD stage is all powered by the battery. In CS stage, as the battery SOC is low, the APU start to provide energy while keep the battery SOC in a reasonable value. How to distribute the power flow among the APU, the battery and the motor plays an important role in reducing the fuel consumption. Assuming reducing the fuel consumption is the goal of control. The optimal problem can be stated as follows:

\[
\min \left[ \int_{t_i}^{t_f} L(x(t), u(t)) \, dt \right]
\]

where $L(x(t), u(t))$ is the cost function. To solve the optimal control problem, the Pontryagin’s minimum principle (PMP) is applied. The PMP is a case of the Euler-Lagrange equation in the Calculus of Variation.

In PMP method, it states that the condition control variable $u^*(t)$ is the optimal solution of the problem is the $u^*(t)$ should meet the following criterias.

Hamiltonian is defined as

\[
H(x(t), u(t), t, \lambda(t)) = \frac{d}{dt} f(x(t), u(t)) + L(x(t), u(t), t)
\]

Then the optimal solution $u^*(t)$ should minimize each instant the Hamiltonian of the problem:

\[
H(x(t), u^*(t), t, \lambda(t)) = \min_{u(t)} H(x(t), u(t), t, \lambda(t))
\]

where $f(x(t), u(t))$ is equation of system dynamic, $L(x(t), u(t), t)$ is the instantaneous cost, $x(t)$ is the state variable, $u(t)$ is the control variable. $\lambda(t)$ is the co-states variable.

The co-states variables should satisfy the following equation:

\[
\lambda(t) = \frac{\partial H(x(t), u(t), t, \lambda(t))}{\partial u}
\]

In REEV energy control problem, the Hamiltonian can be rewritten as:

\[
\min \left[ \int_{t_i}^{t_f} L(x(t), u(t), \lambda(t)) \, dt \right]
\]

where $L(x(t), u(t), \lambda(t))$ is the total required power. To apply the PMP method, the SOC values and the $P_{\text{batt}}(t)$ should fulfill the constrains. The constrains of the $P_{\text{batt}}(t)$ are acquired by the study of different driving conditions in section 3. The $P_{\text{batt}}(t)$ fluctuation range is acquired based on the two specific driving condition in each type. To perform the PMP control, the following optimal condition should follow:

\[
P_{\text{batt}}(t) \leq P_{\text{batt max}} \leq P_{\text{batt min}} \leq P_{\text{batt}}(t) \leq P_{\text{batt mint}} \leq P_{\text{batt min}}
\]

\[
SOC_{\text{min}}(t) \leq SOC(t) \leq SOC_{\text{max}}(t)
\]

\[
SOC_{\text{min}}(t) \leq SOC(t) \leq SOC_{\text{max}}(t)
\]

Once the optimal $P_{\text{batt}}(t)$ is determined, the required engine power can be acquired.
In Figure 7, the process of AICS is illustrated. The AICS mainly consists of two sub-units: the driving condition identifier (DCI) and the power distribution controller (PDC). The DCI accepts the characteristic parameters and determines the most suitable driving condition, then the PDC offers the corresponding optimal power distribution solution. In PDC, the optimal power distribution combinations (the required engine powers and battery powers) based on PMP have been calculated in advance, corresponding to the six different driving cycles and three driving conditions (denoting DC in Fig. 7).

V. SIMULATION AND ANALYSIS

To prove the effectiveness, the simulation by Matlab/Simulink based on a special driving cycle is performed. The effectiveness of proposed advance intelligent control strategy and PMP control strategy without driving condition identifying is compared by analyzing the simulation result of these two control strategies. The special driving cycle is formed by combining the UDDS and the HWFET cycle. The parameters of the vehicle can be seen in Table 3.

### TABLE II Parameters of the REEV

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vehicle mass, $M_{veh}$ (kg)</td>
<td>1315</td>
</tr>
<tr>
<td>Battery peak power, kW</td>
<td>147</td>
</tr>
<tr>
<td>Drag coefficient</td>
<td>0.3</td>
</tr>
<tr>
<td>Battery total energy, kWh</td>
<td>22.6</td>
</tr>
<tr>
<td>Frontal area, $m^2$</td>
<td>2</td>
</tr>
<tr>
<td>Engine nominal power, kW</td>
<td>45</td>
</tr>
<tr>
<td>Rolling resistance coefficient</td>
<td>0.0015</td>
</tr>
<tr>
<td>APU* nominal power, kW</td>
<td>42.5</td>
</tr>
<tr>
<td>Tire radius, m</td>
<td>0.298</td>
</tr>
<tr>
<td>Drive motor power, kW</td>
<td>80</td>
</tr>
</tbody>
</table>

Figure 8 is the curve of the specific driving condition. Figure 9 shows the SOC change of the REEV in CS stage based on the control strategy with driving condition identifying and the control strategy by PMP. It clearly that REEV incorporating control strategy with driving condition
identifying can keep battery SOC at the end of test cycle change smaller compared to the battery SOC at the beginning of the test cycle. In other words, the control strategy with driving condition identifying can keep battery SOC stabilize at a certain value much better than the control strategy without driving condition identifying. Moreover, the simulation result also reveals that the control strategy with driving condition identifying can make battery have stronger discharge ability. Hence, the battery can provide more energy. Fig.10 illustrates the battery power change in the simulation. The graph reveals that the battery discharge and charge power mostly less than 20kw, which is reasonable because battery discharge ability is limited in CS stage. Fig.11 shows the engine torque change and engine operation points in the simulation, the green points are the engine operation points by the AICS while the blue points are the engine operation points by the control strategy without driving condition identifying. From the graph, the engine operating points by the AICS and PMP mostly distribute in lines, which is an optimal engine working curve that is similar with the Brake Specific Fuel Consumption (BSFC) lines. However, the engine operating points by the AICS are more centralized near the BSFC line than that by the PMP. So the AICS make the engine operate in a more optimal way.

In the following study, the information for past driving cycle information, realizing the real-time driving condition identifying together with the method based on the Global Positioning System (GPS) and Geographic Information System (GIS) would be incorporated in driving condition identifying with the method based on the past driving cycle information, realizing the real-time driving condition identifying.

VI. CONCLUSION

In this paper, the control strategy based on driving condition identifying and the optimal control (PMP) for REEV is proposed. This control strategy improves the adaptability of the power distribution to the different driving condition. The proposed control strategy reaps the benefit of LVQ in discerning information and the PMP in offering global optimal solution, providing a feasible method tested in the simulation. In the following study, the information for Global Positioning System (GPS) and Geographic Information System (GIS) would be incorporated in driving condition identifying together with the method based on the past driving cycle information, realizing the real-time driving condition identifying.

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