Abstract
The inaccuracy in remaining driving range (RDR) estimation lowers the consumers’ confidence on electric vehicles (EVs), while one important reason is the inaccuracy in battery residual usable energy (RUE) prediction. Traditionally, RUE is directly estimated based on state of charge (SOC) which could not reflect the energy variation in complex real-world applications. This paper introduces an RDR estimation method through an advanced RUE calculation model (AECM). In AECM, a number of RUE-influencing factors are specifically considered to describe the present energy loss and the available discharge capacity precisely. The future average discharge voltage is real-timely predicted, and the current influence on future energy loss is also considered. To obtain an accurate RUE result in various environmental conditions throughout EV lifetime, the AECM takes into account the influence of state of health (SOH), temperature, and cell inconsistency in battery pack. An accurate RUE value as well as a satisfying RDR could hence be obtained in real-world application. Embedded in a pure electric vehicle, the performance is validated under a set of vehicle experiments on a dynamometer test system. Results show that our RDR method could provide stable and convergent estimation results under different Beijing urban driving conditions, and the estimation error could be rapidly limited to ±5%.

Keywords: Electric vehicle; remaining driving range; battery residual usable energy; advanced energy calculation model; Beijing urban driving cycle

1 Introduction
Electric vehicle (EV) technology is one of the researching focuses in automotive industry owing to its environmental friendliness and low driving cost. However, due to limited energy density and high cost of power batteries, the remaining driving range (RDR) of EV is not competitive, especially for pure electric vehicle without additional power sources. As a result, range anxiety due to inaccurate RDR prediction might be resulted, affecting the consumers’ confidence on PEV. An accurate onboard RDR estimation method is hence crucial for EV acceptance, which is accessible through determining the battery residual usable energy (RUE) and vehicle average energy consumption ($e_{avg}$) in Eq. (1).

$$\text{RDR} = \text{RUE} / e_{avg} \quad (1)$$

In the present RDR-related publications, much attention is paid to the determination of vehicle energy consumption or future driving profile...
prediction. The $e_{avg}$ for onboard RDR function is normally estimated with an adaptive method based on historical data. The prediction of future driving profile as well as the future $e_{avg}$ is also implemented by some researchers to provide more specific information for the present travel [1]. And a combination method with both the adaptive and predictive information was mentioned in [2]. In contrast, the onboard RUE calculation approach is rarely discussed. In real-vehicle application, the remaining energy is normally related to battery state of charge (SOC) in a simple way. However in real-world condition, battery RUE is affected by a set of influencing factors, namely vehicle power demand, battery SOC, aging condition, and operation environment (temperature, mechanical pressure, etc.). A simple RUE model could lead to RDR overestimation or underestimation and the resulted range anxiety is inevitable, indicating a comprehensive RUE model as essential [3]. Additionally, the real-time capability should also be emphasized for an easier onboard application.

This paper presents an onboard RUE model with detailed consideration of real-world operating conditions, i.e. the advanced energy calculation model (AECM). The AECM takes into account a variety of RUE-influencing factors, while the real-time capability is also proved. An RDR calculation model is developed in Matlab/Simulink based on battery AECM, and the performance is further proved on a type of PEV in experimental validation in typical Beijing driving cycle. The remainder of this paper is as follows. The principle and modelling process of battery AECM are introduced in detail in Section 2, and Section 3 shows the experimental setup and onboard model development. Section 4 discusses the model performance in dynamometer test, while Section 5 concludes this paper.

2 Advanced battery RUE calculation method for RDR estimation

As a complex electrochemical system, the battery residual usable energy could vary largely under different real-world operating conditions [4]. However in mainly onboard cases [5], the RUE is directly related to the present SOC, as in Eq. (2), in which $SOC_{end,nom}$, $U_{t,nom}$, and $Q_{bat}$ stand for the nominal end-of-discharge SOC, the nominal battery terminal voltage, and the battery capacity, respectively. It is noticed that all three terms are normally determined as constant in industrial applications, and the energy-influencing operating factors are not much emphasized.

$$RUE_{nom} = Q_{bat} \cdot U_{t,nom} \cdot (SOC - SOC_{end,nom}) \quad (2)$$

The battery RUE could be illustrated in Fig. 1 as the cumulative discharge energy in future operating process [6]. Reflected by the area under terminal voltage curve on the voltage-Ampere hour coordinate system, the RUE depends on the future average discharge voltage $U_{t,avg}$ and the future remaining discharge capacity $Q_{RDC}$. It is revealed that both $U_{t,avg}$ and $Q_{RDC}$ are largely affected by the operating conditions, even at the same SOC. Under larger current demand, lower temperature, or worse state of health (SOH), a lower $U_{t,avg}$ as well as a smaller $Q_{RDC}$ is resulted, indicating reduced RUE. The traditional SOC-based method could hence hardly reflect the RUE variety due to the following reasons. Firstly, a constant nominal terminal voltage $U_{t,nom}$ referencing battery specifications could not reveal battery discharge process. As in Fig.1, the average terminal voltage in battery operating process is dependent on battery charge state. As SOC decreases, a reduced $U_{t,avg}$ is resulted due to decreased voltage level. A different operating condition also affects the $U_{t,avg}$, e.g. under subzero temperature or low SOH condition. Secondly, the end-of-discharge SOC point $SOC_{end,nom}$ and the battery capacity $Q_{bat}$ are also seen as constant, revealing fixed $Q_{RDC}$ at an identical SOC value. For an accurate $Q_{RDC}$ determination, the end-of-discharge point as well as the battery aging state must be taken into account.

![Figure 1: Illustration of the residual usable energy of lithium-ion battery (modified from [6]).](image)

As a result, a comprehensive RUE prediction model is required considering different battery status and operating conditions, so as to guarantee the precision of $U_{t,avg}$ and $Q_{RDC}$ prediction. Eq. (3) shows battery RUE in the presented advanced
energy calculation model (AECM) for onboard application.

$$\text{RUE}_{\text{AECM}} = Q_{\text{RDC,AECM}} \cdot U_{\text{avg,AECM}}$$ (3)

Except for the present SOC, a number of factors should be considered to provide accurate result of average terminal voltage $U_{\text{avg}}$ and remaining discharge capacity $Q_{\text{RDC}}$. In AECM, $U_{\text{avg}}$ is determined in Eq. (4), in consideration of battery state variables (i.e. SOC and SOH), operating conditions (battery temperature condition $T_{\text{bat}}$, current demand $I_{\text{bat}}$, etc.), and cell inconsistency within battery pack (noted as state of inconsistency, SOI). It is also to be noticed that the current demand $I_{\text{bat}}$ in Eq. (4) is determined through the analysis of maximum power demand $I_{\text{max}}$ and average power demand $I_{\text{avg}}$, as in Eq. (5). Additionally, when determining the temperature condition $T_{\text{bat}}$, the future temperature variation delta $T$ due to battery heat generation or environmental change should be included onto the present-measured temperature $T_{\text{meas}}$, as in Eq. (6). As a result, two pre-treating modules for current demand $I_{\text{bat}}$ and temperature condition $T_{\text{bat}}$ is needed in $U_{\text{avg}}$ determination process.

$$U_{\text{avg}} = f(SOC, SOH, I_{\text{bat}}, T_{\text{bat}}, SOI, Q_{\text{st}})$$ (4)

$$I_{\text{bat}} = f(I_{\text{max}}, I_{\text{avg}})$$ (5)

$$T_{\text{bat}} = f(T_{\text{meas}}, \Delta T_{\text{heat}}, \Delta T_{\text{env}})$$ (6)

Meanwhile, the available discharge capacity $Q_{\text{RDC}}$ also needs to be considered as in Eq. (7), in which the influence of various factors is carefully evaluated. Apart from present SOC and the influencing factors, $Q_{\text{RDC}}$ also depends on the standard capacity $Q_{\text{st}}$ in account of battery aging effect. Through a comprehensive set of battery tests under different temperatures, current input, and aging states, the concrete relationship in $Q_{\text{RDC}}$ and $U_{\text{avg,AECM}}$ determination in Eq. (4) and Eq. (7) is obtained. Due to the thorough consideration of performance influencing factors, an accurate RUE result could be expected under different real-world profiles. Additionally, the parameter in AECM is to a large extent based on laboratory calibration result while the complex onboard future voltage prediction process is avoided, the real-time capability in onboard microcontrollers is guaranteed.

$$Q_{\text{RDC}} = f(SOC, SOH, I_{\text{bat}}, T_{\text{bat}}, SOI, Q_{\text{st}})$$ (7)

After determining battery RUE, the remaining driving range (RDR) of electric vehicle could be derived through Eq. (1) based on the average vehicle consumption $e_{\text{avg}}$. The energy calculation is done with an adaptive method based on the previous driving data.

3 Experimental

In this research, a middle-sized electric vehicle on Chinese market was tested for method validation. The PEV was equipped with an energy-type lithium-ion battery pack with 26 kWh, and the distance could be about 160 kilometers in a standard urban driving condition. The driving resistance parameters of the PEV are determined through vehicle sliding experiments, and the vehicle was then tested on a dynamometer test bench to determine the driving range and RDR estimation result under certain driving cycles.

The battery RUE and the vehicle RDR are real-timely obtained in Controller Area Network (CAN). The RDR results are compared with the vehicle real remaining range reversely-integrated from the end point of this travel. A type of prismatic NCM-G battery which is implemented in the specific EV is calibrated in our lab. The battery is with a nominal capacity of 20 Ah. A Digitron BTS-600 testbench with current range -100~100 A was implemented to charge and discharge the battery, with a Puhua TEMI880 temperature chamber to control the temperature. The battery basic parameters (open-circuit voltage, resistance, etc.) as well as the performance under different temperature and aging conditions are investigated experimentally to provide the calibration data for the AECM and the RDR calculation process.

In this paper, a set of Beijing typical urban driving cycle (BTUDC) was implemented to determine the RDR estimation performance of the PEV in the typical Chinese metropolitan application. Two types of driving cycles, i.e. the Beijing peak-hour typical driving cycle (BPTDC) and the non-peak hour typical driving cycle (BNTDC), are individually employed for vehicle RDR test. The RDR result is then analysed to validate the performance. The typical driving cycle is based on the real-vehicle collected data from the volunteer passenger cars in Beijing, with the generated the generated BNTDC with 1207-seconds time length, 81 km/h maximum speed, and a distance of 6.97 km, as in Fig. 2. In contrast in Fig. 3, the case for non-rush hours (i.e. the BNTDC) is shown with 1050-seconds time length, 80 km/h maximum speed, and a distance of 4.79 km.
4 Results validation

The selected PEV was tested on the dynamometer under typical Beijing driving conditions with different traffic conditions, i.e., the Beijing peak hour typical driving cycle (BPTDC) and the Beijing non-peak hour typical driving cycle (BNTDC). In the BNTDC test, the vehicle was firstly fully charged and rested for more than three hours, and a total of 19 consecutive cycles are accomplished. A total of 138 km driving distance is achieved. In the limp-home status, the vehicle could still cover another 10 km before the final energy expiration.

During the test, the battery remaining usable energy was calculated through the presented AECM method, and then used for the vehicle RDR calculation through Eq. (1). The real-time calculated RDR is compared with the real remaining range to validation the onboard performance. The real RDR is obtained by integrating the real driving distance between the current time point and the limp-home time. For instance, the real RDR at the start equals the total distance of the test, i.e., 138 km. Result is shown in Fig. 4, with the blue curve representing the estimation result and the red curve for the real value. An obvious RDR error is observed in the initial driving period, but the estimation result converge rapidly towards the real value and guarantees high accuracy in the rest period. The initial error is due to the limitation of adaptive consumption calculation, as the vehicle operates in the present condition (i.e., BNTDC), the consumption value $e_{avg}$ gradually approaches the real value, and the RDR result is optimized.

In order to simulate the driving condition with free hour followed by peak hour, another case was investigated by combining the normal-hour BNTDC with the rush-hour BPTDC. Twelve cycles of BNTDC were firstly employed, and then the BPTDC representing the peak hour was driven for 11 cycles until the limp-home mode. The total driving distance is 132 km, and the results are compared in Fig. 5. It is shown that the RDR accuracy on the entire driving process is satisfying, but the estimation value in the former part is a little bit higher than the real value. It is probably because that the latter part (BPTDC) is related to larger energy consumption than the former part, and the consumption is underestimated at the beginning, as the change of driving profile is not predictable in the adaptive energy consumption method. And the RDR is hence overestimated according to Eq. (1). In general, the RDR estimation result is satisfactory in combined urban conditions.
5 Conclusion

Remaining driving range (RDR) estimation is one of the key functional issues of electric vehicles, but the RDR estimation performance is greatly influenced by the prediction accuracy of battery residual usable energy (RUE). An RDR estimation method through an advanced RUE calculation model (AECM) is presented in this paper, in which a comprehensive investigation of RUE-influencing factors is specifically considered to describe the available discharge capacity. To obtain an accurate RUE result in various environmental conditions throughout EV lifetime, the AECM considers the influence of state of health (SOH), temperature, and cell inconsistency in battery pack. An onboard RDR estimation method is then developed based on the battery RUE model. In a type of pure electric vehicle, the performance is validated under a set of vehicle experiments in dynamometer test. Results show that our RDR method could provide stable and convergent estimation results under different Beijing urban driving conditions, including non-peak hour driving condition, and a combined condition with different traffic cases.

6 References


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