Factors Affecting the Accuracy of Estimation of BEV Cruising Range

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Abstract. As the number of electric vehicles is increasing year by year, the accuracy of electric vehicle cruising range estimation in high and low temperature environments is one of the performances that consumers are very concerned about. In this paper, the accuracy of cruising range estimation is evaluated by the determination of coefficient, and the influence of ambient temperature on the estimation accuracy of cruising range is deeply studied. Eleven electric vehicles were selected to carry out the cruising range test at normal temperature, high temperature and low temperature respectively, and the influence law of ambient temperature on the accuracy of cruising range estimation was obtained. At the same time, the influence of the self-learning function on the accuracy of the cruising range estimation is also studied. Finally, the performance of the estimation of accuracy of the end mileage at different ambient temperatures is analyzed.

Keywords: environment temperature; electric vehicle; range; range estimation accuracy; coefficient of determination

1. Introduction

China's new energy vehicle market has developed rapidly. By the end of June 2018, the number of new energy vehicles reached 1.99 million, of which 1.62 million were pure electric vehicles, accounting for 81.4% of the total number of new energy vehicles. Compared with fuel vehicles, electric vehicles have fast speed response, no pollution emissions, and low noise, but the virtual cruising range of electric vehicles is limited by battery capacity and power density. The cruising range, especially the cruising range at low temperature, is one of the performance indicators that electric vehicle consumers pay attention to [1].

Compared with traditional fuel vehicles, the range of electric vehicles is greatly affected by the ambient temperature. Studies have shown that temperature can affect battery life, mainly because ambient temperature can affect battery capacity. The capacity retention of the lithium battery at 0°C is 60% to 70%, 40% to 55% at 10°C, and only 20% to 40% at 20°C [2-3]. China has a vast territory, about 5,500 kilometers from north to south, and about 5,000 kilometers from east to west. Therefore, China has both a warm tropical climate and a plateau with snow all year round. Even if the temperature difference between different regions may become larger at the same season, it is important to study the...
adaptability of vehicles at different temperatures.

During the actual use of electric vehicles, the meter shows that the remaining cruising range is another very important parameter, and the estimated accuracy of range can greatly reduce the driver's range anxiety[4]. However, the accurate or not range displayed on the dashboard, there is no unified evaluation standard at home and abroad. Therefore, it is necessary to carry out systematic research and establish an objective and feasible evaluation standard to evaluate it.

2. Experiment method

In this test, according to the "EV-TEST Management Rules" [5], the range test is divided into normal temperature range (25°C), high temperature range (35°C) and low temperature range(-7°C). Before performing the corresponding durability test, it must soak the vehicle in the corresponding environment for 12h to 36h, and then the NEDC condition test is conducted cycled. In the high temperature or low temperature durability test, the air conditioner needs to be turned on. In the high temperature range test, the internal temperature should be maintained between 23° C and 25° C. For low temperature range tests, the internal temperature should be maintained between 20° C and 22° C. The test of estimated cruising range accuracy and range test should be performed simultaneously.

2.1. Vehicle parameters

In this test, 8 vehicles with a body length of 4 m or more (conventional vehicle) and 3 vehicle bodies less than 4 m (mini vehicle) were selected. The vehicle parameters are shown in Table 1.

| Vehicle model | Curb quality (kg) | Range (km) | Battery capacity(kw•h) |
|---------------|------------------|------------|-----------------------|
| 1             | 1564             | 351        | 49                    |
| 2             | 1710             | 320        | 48.3                  |
| 3             | 1470             | 270        | 36                    |
| 4             | 1410             | 301        | 38.5                  |
| 5             | 1950             | 300        | 47.5                  |
| 6             | 1598             | 300        | 41                    |
| 7             | 2160             | 352        | 62                    |
| 8             | 1610             | 200        | 30                    |
| 9             | 1080             | 255        | 22                    |
| 10            | 1175             | 151        | 29.2                  |
| 11            | 855              | 151        | 18.2                  |

2.2. Experimental procedure

![Test procedure](image)

Figure 1. Test procedure.
The test process is shown in Figure 1. On the drum test rig, when the test cut-off condition is reached, the test under NEDC conditions is stopped[6]. When testing, record the remaining range displayed by the meter before the start of the test (data point of the 0th cycle) and the remaining range displayed by the meter at the end of each complete NEDC condition. When an NEDC condition is completed, a data is recorded, and after the test is completed, the actual remaining range corresponding to each the remaining range of meter is calculated based on the actual cruising range.

2.3. Determination of coefficient
In order to assess the accuracy of the actual remaining range display, it is necessary to convert it from a practical problem to a mathematical model to take the actual remaining range measured on the drum as a regression line and use the remaining range displayed on the dashboard as a dispersion point. In this way, the cruising range estimation accuracy problem is converted into the goodness of fit between the regression line and the scatter point. In this paper, the accuracy coefficient $R^2$ in statistics is used to evaluate the range estimation accuracy.

Determination of coefficient: A numerical feature that represents the relationship between a random variable and multiple random variables. It is a statistical indicator used to reflect the reliability of the regression model's dependent variable [7].

The physical meaning of the Determination of coefficient is as shown in Figure 2. $\hat{y}_i$ indicates the actual remaining range, which is a regression line, and $y_i$ indicates the remaining range displayed by the meter, which is the observed value.

![Variational decomposition diagram](image)

Figure 2. Variational decomposition diagram.

Total sum of squares is: $\text{SST} = \sum (y_i - \bar{y})^2$ (1)

Sum of residuals is: $\text{SSE} = \sum (y_i - \hat{y}_i)^2$ (2)

Regression square sum is: $\text{SSR} = \sum (\hat{y}_i - \bar{y})^2$ (3)

The relationship between the three squares is:

$$\text{SST} = \text{SSR} + \text{SSE}$$ (4)

After derivation, the formula for determining the coefficient $R^2$ is:

$$R^2 = 1 - \frac{\text{SSE}}{\text{SST}} = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y})^2}$$ (5)

The closer $R^2$ is to 1, the larger the ratio of the sum of the squares of the regression to the total square sum, the closer the regression line is to each observation point, the better the fit of the regression line; on the contrary, the closer $R^2$ is to 0, the regression line The degree of fit is worse. When $R^2 \leq 0$, it is considered that the regression line seriously deviates from the observed value, that is, the degree of fitting is extremely poor.
3. Range estimation accuracy

The remaining range and actual remaining range displayed by the meter of the electric vehicle are recorded in the experiment. The range displayed by the meter tested in the normal temperature environment is indicated by CB, and the actual remaining range is represented by CS. The range displayed by the meter tested in a high temperature environment is expressed in GB, and the actual remaining range is expressed in GS. The range displayed by the meter tested in a low temperature environment is indicated by DB, and the actual remaining range is represented by DS.

3.1. Test results of type some vehicles

Figure 3 shows the range test data of vehicle 10. It can be seen from the above three figures that the difference the range displayed by the meter and the actual range are very small in different temperature environments. And the best performance occurs in the high temperature environment. R^2 is highest at high temperatures and lowest at low temperatures.

Figure 4 shows the results of the range experiment of the vehicle 7. It can be seen from the figure that the remaining range displayed by the meter in the vehicle 7 is not much different from the actual remaining range. In the low temperature environment, the difference between the remaining range displayed by the meter and the actual remaining range is large. R^2 is highest at normal temperature and lowest at low temperature.

![Figure 3](image-url) Cruising range of No. 7 vehicle model at different temperatures.

![Figure 4](image-url) Cruising range of No. 7 vehicle model at different temperatures.
3.2. Determination of coefficient of each vehicle type at different temperatures

Figure 5 shows the $R^2$ values of eleven types of vehicles at different temperatures. The average $R^2$ of the eleven types of vehicles is 0.88. Among them, the $R^2$ of eight types of vehicles is greater than 0.9 and the overall performance is good.

![Graph showing $R^2$ values for eleven types of vehicles at normal temperature.](image)

**Figure 5.** Comparison for $R^2$ of eleven type of vehicles under normal temperature.

The determination of coefficient of the vehicle 11 at high temperature is less than 0, so the cruising range estimation accuracy of the vehicle 11 in the high temperature environment is the worst. Figure 6 shows the Determination of coefficients of the remaining vehicles at high The average of $R^2$ for 10 types of vehicles is 0.81. Among them, only 5 types of vehicles have $R^2$ greater than 0.9, and vehicle performance begins to show a gap.

![Graph showing $R^2$ values for ten types of vehicles at high temperature.](image)

**Figure 6.** Comparison for $R^2$ ten types of vehicles under high temperature.

The Determination of coefficients of the vehicle 3, vehicle 5 and vehicle 9 in the low temperature environment are less than 0, indicating that the cruising range estimation accuracy of the three types of vehicles in the low temperature environment is very poor. Figure 7 shows the Determination of coefficients for the remaining eight vehicles in a low temperature environment. The average $R2$ of these 8 vehicles is 0.46, and only $R2$ of the only 2 vehicles is greater than 0.9, and the overall performance is poor.

![Graph showing $R^2$ values for eight types of vehicles at low temperature.](image)
3.3. The effect of self-learning on the Determination of coefficient

In order to improve the accuracy of cruising range estimation, some enterprises have added self-learning function in the control strategy, which can correct the current remaining range according to historical energy consumption, thereby improving the accuracy of the remaining range displayed by the meter [8-9]. In order to study the effect of self-learning function on the accuracy of cruising range estimation, this paper removes the data of the first two cycles by comparing and calculating, and collects data from the third cycle. The equivalent effect is to reserve a self-learning distance of approximately 22 km (approximately 11 km for an NEDC cycle) for the vehicle.

Figure 8 shows the ratio of $R^2$ between after the first two cycles and the total cycle of the eleven models in the normal temperature environment. As can be seen from the above figure, after removing the first two cycles in the normal temperature environment, $R^2$ becomes larger or smaller, and the average decreases by 5%. The accuracy of vehicle 10 and vehicle 11 varies greatly, both fell by more than 24%.

Figure 9 shows the ratio of $R^2$ of the ten type vehicles between after the first two cycles removed and all cycles in the high temperature environment, the $R^2$ of the vehicle 11 is less than zero. The $R^2$ of the ten vehicles dropped by an average of 3.9%. Among them, $R^2$ of the types of vehicle 1 and vehicle 3 changed a lot, the accuracy dropped by more than 15%, and the others changed within 4%.
Figure 9. Change of ten types of vehicles after removing the first two cycles under high temperature.

Figure 10 is a plot of $R^2$ for the first two cycles and all cycles removed in a low temperature environment. Among the eleven models, the $R^2$ of the vehicle 2, vehicle 3, vehicle 4, and vehicle 11 is less than 0. It can be seen from the above figure that the determination of coefficient of the seven types of vehicle has averagly dropped to 18.7%. The variation of the 6 and 9 types of vehicle is larger, the $R^2$ is reduced by more than 40%, and the variation of others is within 6%.

Figure 10. Change of seven types of vehicles after removing the first two cycles under low temperature.

It can be seen from the above data that the removal of the first two cycles has little effect on $R^2$ and does not change the overall result range. Therefore, whether the vehicle is equipped with a self-learning function has less influence on the result.

3.4 Estimated accuracy of the end range

When the battery power is low, the range anxiety of the electric vehicle driver is particularly prominent. This paper further studies the cruising range accuracy when the battery is low.
Figure 11 shows the Determination of coefficient $R^2$ of the last four cycles of vehicle 7 at normal temperature, and the end range $R^2$ of the vehicle 5, vehicle 8, vehicle 9 and vehicle 10 is less than zero. It can be seen from the above figure that the Determination of coefficient of the vehicle 7 has dropped by an average of 36.7%. Among them, the coefficient of determination of vehicle 2 dropped the least, down 20%, and the coefficient of determination of vehicle 7 dropped the most, down by 67.9%.

![Figure 11. Determination of coefficient of the last four cycles in normal temperature.](image1)

Figure 12 shows the end range $R^2$ of vehicle 5 in a high temperature environment. The end range $R^2$ of other types of vehicle is less than zero. As can be seen from the above figure, the $R^2$ of the 5 types of vehicle decreased by an average of 29.7%, of which the vehicle 10 changed the most, the $R^2$ decreased by 72.0%, the vehicle 8 changed the least, and the $R^2$ increased by 0.37%.

![Figure 12. Determination of coefficient of the last four cycles in high temperature.](image2)
Figure 13 shows the end range $R^2$ of the two types of vehicle in a low temperature environment. The end range $R^2$ of others is less than zero. The $R^2$ of the two types of vehicle dropped by an average of 62.9%.

It can be seen from the above data that the $R^2$ of the end range of the electric vehicle is lower than that of the whole cycle $R^2$, and the $R^2$ in the low temperature environment is more decreased. Under low battery power conditions, vehicles generally do not provide accurate range estimates, which will increase the range anxiety of electric vehicle drivers.

4. Conclusion
The range estimation accuracy of electric vehicles at different ambient temperatures is also different. The normal temperature is the best, the high temperature is second, and the low temperature is the worst. In the normal temperature, the determination of coefficient of nine types of vehicle reached 0.9, and the determination of coefficient of only five types of vehicle in the high temperature reached 0.9, and the determination of coefficient of only two types of vehicle in the low temperature reached 0.9. It is small impact to the overall result that eliminating the influence of the self-learning function. So all data points can be directly collected when evaluating the accuracy of the cruising range estimation.

The end range estimate $R^2$ is greater than the $R^2$ of all cycles, and even some models have $R^2$ less than 0, which leaves a great space for the automotive industry to improve the accuracy of the end range estimation.

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