Analysis of Factors Affecting the Accuracy Evaluation of Range Estimation of Pure Electric Vehicles Based on CLTC-P

Feifei Wang, Tianlu Dai, Xiaobing Zheng, Xiaolong Pan, Ligang Lei
China Automotive Research & Center Co, Tianjin 300300
daitianlu@catarc.ac.cn

Abstract: The estimation accuracy of the cruising range of electric vehicles is an important performance index of electric vehicles. Improving the accuracy of cruising range estimation is of great significance for improving the user acceptance of electric vehicles. This paper carried out vehicle tests under normal temperature environment based on China light-duty vehicle test cycle for passenger car (CLTC-P) under different battery state of charge and long-distance constant-speed driving, and use the determination coefficient to analyze and evaluate the accuracy of the metered range mileage. At the same time the paper deeply study the impact of different data collection frequencies and the vehicle's metered range self-learning mode on the accuracy of the range mileage. This study provides theoretical support for the use of certain coefficients to study the accuracy of the estimated range of pure electric vehicles under unified scenarios and specific working conditions, and to establish a test and evaluation method for the accuracy of range of electric vehicles.

1. Foreword
As various technologies of electric vehicles become more mature, electric vehicles are gradually used by consumers. However, the performance of batteries has become the main reason for restricting the promotion of pure electric vehicles. According to consumer surveys, in the satisfaction scores of battery performance indicators and battery life indicators, the remaining mileage display accuracy scores are not satisfactory for two consecutive years (2018 and 2019). The score in 2018 is shown in Figure 1[1]. Remaining display accuracy is one of the indicators that consumers are more concerned about but have lower satisfaction, which has a larger room for improvement.

Due to the low accuracy of the remaining mileage display, some vehicles show that there is still a certain amount of mileage that can be driven when the State of Charge (SOC) is relatively low, but the vehicle cannot drive because of insufficient power, which caused consumers' "mileage anxiety". Therefore, it is of practical significance to study the accuracy of the estimated range of pure electric vehicles in the unified scene and specific working conditions, so as to relieve consumers’ anxiety about the mileage of electric vehicles[2-4], and promote the development of the entire electric vehicle industry.
This paper selects four factors, such as different data collection frequency, different battery state of charge, self-learning mode of displayed mileage and long-distance constant speed driving, to analyze and compare the influence of the estimation accuracy of driving mileage.

2. Test method and data processing

In order to evaluate the objective accuracy and the consistency of the environment, the laboratory working condition method is preferred to test the estimated accuracy of the cruising range.

2.1. Test plan

This article chooses to test the evaluation accuracy of the driving range of electric vehicles based on the CLTC-P under normal temperature environment. The speed curve of the CLTC-P is shown in Figure 2.

![Speed curve of CLTC-P](image)

The test is divided into 4 groups: the processing and analysis of the test data at different collection frequencies; the test and accuracy calculation of the vehicle under different SOC conditions; the calculation and analysis of the remaining mileage accuracy of the vehicle reserved self-learning process; the accuracy of the test under long-distance constant speed combined working conditions, which is shown in Figure 3.

![Composite test conditions](image)

2.2. Calculation of mileage accuracy

During the test, record the remaining mileage of the vehicle during driving and record it as $y_1$. The actual mileage of the vehicle is calculated by subtracting the vehicle's driving mileage and time integral from the vehicle's final mileage to calculate the actual remaining mileage of the vehicle, which is recorded as $\hat{y}_1$. According to the comparison of the actual mileage and the collected cruising mileage data of the meter display, the relationship between the actual remaining mileage of the electric vehicle and the remaining mileage of the meter display is analyzed. The paper establish the corresponding mathematical models, and obtain the cruising range accuracy according to the best fitting goodness evaluation. This paper uses the determination coefficient $R^2$ to evaluate the goodness of fit evaluation\cite{5}, the calculation formula is:

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

The closer $R^2$ is to 1, it indicates that the better the fitting degree, the higher the accuracy of the cruising range estimation. On the contrary, the closer $R^2$ is to 0, the worse the fitting degree, and the
worse the accuracy of the cruising range estimation. When $R^2 \leq 0$, it is considered that the degree of fitting is extremely poor, indicating that the displayed cruising range has relatively lost reference significance.

3. The test results of the accuracy of cruising range estimation under the influence of different factors

3.1. Differences in $R^2$ at different data collection frequencies

Different test data collection frequencies has a certain influence on the calculation result of cruising range estimation accuracy $R^2$.

Figure 4 shows that when a certain vehicle type is tested, the vehicle travels 5km, 10km, 14.48km (a driving distance of a CLTC-P) at intervals, and records the corresponding cruising range.

First, in the same experiment, the higher the frequency of observation points, that is, the larger the amount of data for calculating $R^2$, the calculated $R^2$ value will be relatively smaller, that is, the higher the calculation accuracy. The reverse is also true. Under normal temperature, $R^2_{5km} < R^2_{10km} < R^2_{14.48km}$, which are caused by different calculation data.

Secondly, when the value of $R^2$ is higher, the effect of the observation frequency on the value of $R^2$ is smaller. The reverse is also true. when the amount of data is doubled, the calculated $R^2$ value decreases by 0.77%.

![Figure 4 R^2 under different data collection frequencies of a certain vehicle type](image)

In general, the higher the frequency of values, that is, the larger the amount of data used for calculation, the higher the calculation accuracy of $R^2$. There is a non-linear relationship between the amount of data and the calculation accuracy, there is a marginal effect, in the actual test, the frequency of the observation point can be selected according to the actual situation and needs.

3.2. Evaluation test results of vehicle mileage estimation accuracy $R^2$ under different SOC conditions

Test results show that the estimated accuracy of the cruising range varies under different states of charge (SOC), that is, when the remaining power is different.

![Figure 5 Estimated accuracy of cruising range of different SOC segments of 9 models](image)

Figure 5 is a comparison of the estimated accuracy of the cruising range of nine models based on CLCT-P in different SOC segments. It can be seen from that the estimation accuracy of the cruising range of all vehicles decreases with varying degrees as the SOC decreases. It shows that in the low SOC segment, it brings greater mileage anxiety and a worse driving experience to electric vehicle drivers.

In addition, different models have a certain degree of difference in the accuracy of the range estimation accuracy as the SOC decreases. There are four models with small differences in the accuracy of range estimation under different SOCs, indicating that the vehicle shows a more accurate range...
estimation under any state of charge. There are three models with different SOCs. Model 6 has a very large differentiation, which is a negative value when the SOC is 30%, indicating that the vehicle's cruising range in the case of low power does not have a reference value. The above conditions are all related to the algorithm logic and display strategy of the vehicle table display cruising range estimation.

3.3. The influence of mileage estimation self-learning mode on the determination coefficient

The self-learning mode of displaying mileage estimation is one of the strategies of many car companies to improve the accuracy of cruising range estimation. The main method is that the vehicle corrects the current remaining mileage according to the historical driving or the energy consumption of the first half of a journey, in order to improve the accuracy of displaying the remaining mileage[6-8].

In order to study the influence of the self-learning mode on the estimation accuracy of cruising range, in view of the consistency of the test data collection, this article initially proposes to remove the data of the first two driving cycles and start collecting data after the third cycle. The equivalent effect is to reserve a self-learning distance of about 30km (one CLTC-P cycle is about 14.48km) for the self-learning distance.

Figure 6 Changes after removing the first two cycles at normal temperature

Figure 6 selects four models to perform the CLCT-P test under normal temperature environment, and compares the R² of the four models after removing the first two cycles with the estimated accuracy R² of the cruising range of all cycles. As can be seen from the figure, the R² of the four models has improved after removing the first two cycles and the R² increased by an average of 0.79%, of which model 2 and model 3 R² increased by 1.2% and 1.9%, respectively larger.

It can be seen from the above data that the four models all use the self-learning mode in the cruising range estimation strategy. This mode has improved the accuracy of the cruising range estimation to a certain extent, but the improvement is relatively small. This is because the self-learning mode adopted by car companies generally corrects the current remaining mileage according to the historical energy consumption of a longer distance. And the self-learning mode is not sensitive to changes in shorter driving conditions. In this way, it is avoided that the remaining mileage estimate shows a large jump based only on the short-term actual driving road conditions of the vehicle, thereby giving the driver an "artifact" of inaccurate mileage display and unnecessary mileage anxiety.

3.4 Analysis of the effect of long-distance constant speed on the estimation accuracy of cruising range R²

A composite working method speed segment consisting of 2 test cycle sections and 2 constant speed sections is constructed. Among them, DS1 and DS2 are test cycle sections, which are composed of CLTC-P; CSSM and CSSE are constant speed sections, which are composed of higher constant vehicle speeds. For the estimation accuracy of cruising range, it is obviously equivalent to adding jump evaluation points (as shown in Figure 3).

Figure 7 shows the comparison of the test results of the estimated accuracy R² of the cruising range of the three models under the full working condition and the composite conditions method based on the constant speed section of 100km/h. As can be seen, the three models show a higher range accuracy R² in all single CLCT-P. The typical accuracy under the compound operating conditions is because of the existence of three trip points, the estimated accuracy R² of cruising range has been significantly reduced. The three models with the largest decrease in accuracy R² are model A (-18.51%) and the smallest are model B (-10.08%), the average decrease is 14.61%. It shows that the composite working
conditions bring higher requirements to the accuracy of cruising range estimation.

![Estimation accuracy of full condition and composite condition](image)

Figure 7 Estimation accuracy of the full condition and the composite condition

4. Conclusion
Based on CLCT-P, this paper carried out experimental tests and analysis and comparison on the impact of various factors such as different data collection frequencies, different battery state of charge, meter display mileage self-learning mode, and long-distance constant speed driving on the accuracy of continuous mileage estimation. And the following research results are obtained.

1. The test table shows that the frequency of observation points for the estimation accuracy of cruising range has an influence on the calculation accuracy of the estimation accuracy of cruising range $R^2$. The larger the amount of data, the higher the calculation accuracy of $R^2$. However, there is a marginal effect on the nonlinear relationship between the amount of data and the calculation accuracy. In actual experiments, the frequency of observation points can be selected according to the actual situation and needs;

2. The estimation accuracy of the vehicle's cruising range decreases as the SOC decreases. The lower the SOC, the lower the accuracy of the cruising range estimation. The $R^2$ of different vehicle models differs with the degree of SOC decline, which is mainly related to the algorithm logic and display strategy of the vehicle range display range estimation.

3. Tests show that the self-learning mode will be adopted to improve the accuracy of the estimated driving range estimation. And the accuracy of range estimation has a positive impact on accuracy of the estimated driving range.

4. Because of the existence of three trip points of compound operating conditions, the average decrease in the estimated accuracy $R^2$ of the test vehicle is 14.61%, which has greater impact.

By analyzing the influencing factors of the estimation accuracy of cruising range, this paper provides a certain reference significance for improving the accuracy. The paper can further research the development of computing logic and display strategies, which will approach consumer needs, provide consumers with accurate mileage reference, and reduce mileage anxiety.

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