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Development and Validation of a Range Prediction Model for New Energy Vehicles

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Abstract. Given the significant discrepancy between the official driving range of new energy vehicles and users' real-world experience, this paper analyzes the range attainment rate by considering three key factors: ambient temperature, driving speed, and air-conditioning operation. To address this issue, this study collects and preprocesses real-world test samples from media platforms such as Autohome and Dongchedi, combines them with official test reports from the China Automotive Technology and Research Center (CATARC), and constructs a range prediction model based on multiple linear regression. The empirical results reveal that ambient temperature acts as the dominant factor influencing driving range variation, contributing to nearly 40% of total range attenuation, while high-speed driving and air-conditioning operation also significantly increase vehicle energy consumption. Across several test scenarios, the coefficient of determination (R^2) remains at 0.84, and the prediction residuals fall within a 15% error band. These results show that the proposed model can partially correct the prediction bias in traditional NEDC/CLTC standards under extreme operating conditions. It also provides a quantitative basis for driving decisions under complex conditions and may improve users' confidence in trip planning.

Keywords: New energy vehicles, range prediction, multiple linear regression, mathematical modelling, data analysis

1. Introduction

The market share of new energy vehicles continues to rise, yet a notable gap remains between the officially rated driving range and users' real-world driving performance. This "range gap" is still one of the main practical problems facing the industry. Current test standards, including CLTC and NEDC, are largely based on ideal laboratory temperature control and fixed speed distributions. They therefore fail to reflect the fluctuation mechanism of energy consumption under complex real-world driving conditions. In real-world use, especially during cold winters in northern regions, diminished electrochemical activity of traction batteries, coupled with the demand for cabin heating, leads to a substantial drop in the range achievement rate. At the same time, aerodynamic drag increases with the square of vehicle speed during highway driving, further intensifying energy-consumption variation. This lack of visibility in range performance increases the burden of user decision-making and limits the applicability of new energy vehicles across different use scenarios.

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Existing approaches to range prediction mainly include standardized laboratory tests such as NEDC, CLTC, and WLTP, mechanism-based energy-consumption models, and data-driven methods. The first two types have theoretical grounding and interpretability, but are limited by mismatches between test cycles and real-world conditions and by the difficulty of parameter calibration. Although data-driven methods can uncover hidden patterns, their "black-box" nature and strong dependence on data limit their wider application. By contrast, multiple linear regression built on real-world test data boasts low computational complexity, straightforward interpretability and satisfactory prediction accuracy. It is therefore useful for engineering tasks where only a small dataset is available, and a practical model is needed quickly.

Against this background, this study uses multidimensional regression analysis to model the range attainment rate under complex driving conditions. It integrates multi-source real-world test data, quantifies the impacts of core factors including ambient temperature, driving speed and auxiliary power load, and develops a practical dynamic driving range prediction model. The aim is to improve the reliability of range estimation and reduce users' range anxiety.

2. Related work

Existing studies on new energy vehicle range prediction can be grouped into three areas: energy-consumption modelling, environmental impact analysis, and prediction algorithms.

In energy consumption modelling, Fiori et al. constructed a power-based energy consumption model based on vehicle dynamics, which correlates vehicle operating conditions with energy consumption [1]. Björnsson and Karlsson examined the effect of low temperatures on electric vehicle energy consumption and range estimation under Nordic climate conditions, showing the role of thermal management systems in extreme climates [2]. Yuksel and Michalek further explained the nonlinear effect of regional temperature differences on electric vehicle efficiency [3].

In environmental impact analysis, Zhang et al. found that driving range may fall by more than 30% under low-temperature conditions [4]. Wu and Freese built an electric vehicle energy consumption prediction model using road data, and stressed the coupling relationship between road conditions and driving cycles [5]. In China, the China Automotive Technology and Research Center issued technical specifications for winter range testing of new energy vehicles, which provide methodological guidance for standardized real-world testing [6]. User survey reports also show that the range attainment rate has become a primary factor affecting user satisfaction [7].

In prediction algorithms, traditional physical models are interpretable but have limited ability to describe multivariable coupling. Machine learning methods represented by neural networks are capable of capturing nonlinear characteristics, while high data dependency and poor interpretability hinder their rapid engineering deployment. Yao et al. used linear programming to optimize electric vehicle charging schedules, confirming the practical value of linear models in energy-efficiency optimization [8]. Montgomery et al. noted in their regression analysis text that multiple linear regression is intuitive and reliable when dealing with multivariable coupling, making it one of the standard tools for engineering prediction [9].

3. Data sources and preprocessing

The dataset was drawn from three sources: Dongchedi's winter and summer range tests, Autohome's real-world vehicle test database, and official test reports released by the China Automotive Technology and Research Center (CATARC). It includes ten valid observations from five widely used new energy vehicle models: the BYD Dolphin, Tesla Model 3, NIO ET5, XPeng P7, and

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Wuling Hongguang MINI. The observations cover a range of practical driving conditions, with ambient temperatures from -5°C to 30°C, average speeds from 35 km/h in urban driving to 120 km/h on highways, and both air-conditioning-on and air-conditioning-off cases. Such comprehensive data coverage enables the proposed model to capture variations in driving range performance under different temperature, speed and auxiliary power load conditions, as presented in Table 1.

Table 1. Summary of sample data

Vehicle model	Official range	Tested range	Temperature	Speed	Attainment rate
BYD Dolphin	420 km	380 km	25°C	45	90.5%
Tesla Model 3	556 km	420 km	-5°C	60	75.5%
Wuling Hongguang MINI	170 km	145 km	20°C	35	85.3%
NIO ET5	560 km	480 km	30°C	50	85.7%
XPeng P7	586 km	450 km	10°C	80	76.8%

Before building the model, the key variables were first examined through scatter plots and Pearson correlation analysis. The results show that temperature is positively correlated with the range attainment rate ($r = 0.72$), while vehicle speed and air-conditioning operation are negatively correlated with it ($r = -0.58$ and $r = -0.45$, respectively). This finding indicates that ambient temperature exerts the most prominent impact on driving range performance among all explanatory variables. When the ambient temperature falls below 10°C, the range attainment rate decreases noticeably. This variation trend aligns with diminished battery electrochemical activity under low-temperature conditions and extra power consumption required by vehicle thermal management systems.

4. Methodology

4.1. Analysis of key factors affecting range

Based on real-world test data, this study focuses on four factors that clearly affect vehicle range.

Ambient temperature: Temperature changes directly affect battery performance. Under low-temperature environments, lithium-ion migration inside batteries declines, accompanied by a rise in internal ohmic resistance. The vehicle also needs extra energy to heat the battery pack and the cabin. In winter conditions, the PTC heating system may draw about 3–5 kW continuously, which becomes one of the main sources of range loss.

Aerodynamic drag: Vehicle speed strongly affects energy consumption. As aerodynamic drag varies in proportion to the square of vehicle speed, highway operation consumes far more electric power than driving at low and medium speeds. The test data show that energy consumption rises sharply once the vehicle exceeds the relatively efficient speed range of 40–60 km/h.

Thermal management and air conditioning: The air-conditioning and thermal-management systems add a noticeable auxiliary load. Their power demand varies by season, usually ranging from about 1 kW to 5 kW. In very cold weather, auxiliary systems can account for more than 25% of a vehicle's total energy consumption.

Driving mode: Change how the motor responds to acceleration and releases torque. For example, economy mode limits power output to reduce energy consumption, while more aggressive driving modes increase power demand. As a result, different driving styles and control settings may cause energy-efficiency differences of more than 10%.

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4.2. Construction of the multiple linear regression model

Multiple linear regression is a classical statistical method for analysing the linear relationship between several independent variables and one dependent variable. This study specifies the following model:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \varepsilon \tag{1}$$

where Y is the range attainment rate (%), X_1 is ambient temperature (°C), X_2 is average vehicle speed (km/h), and X_3 is the air-conditioning state (1 = on, 0 = off). β_0 is the intercept, β_1, β_2, and β_3 are regression coefficients, and ε is the error term.

Ordinary least squares (OLS) was adopted to estimate the regression coefficients of the constructed prediction model. OLS minimizes the sum of squared residuals between the predicted and observed values, thereby producing the optimal parameter estimates under the linear model.

5. Results

5.1. Estimation of regression coefficients

The INTERCEPT and SLOPE functions in Excel were used to calculate the regression coefficients. The results are shown in Table 2.

Table 2. Regression coefficient estimates

Coefficient	Value	Interpretation
β_0 (intercept)	92.5	Baseline range attainment rate (%)
β_1 (temperature)	+0.42	Change for each 1°C increase in temperature
β_2 (speed)	-0.18	Change for each 1 km/h increase in speed
β_3 (air conditioning)	-5.2	Effect of air-conditioning use (%)
R^2	0.84	Explanatory power of the model

The final model is expressed as follows:

$$Y = 92.5 + 0.42T - 0.18v - 5.2AC \tag{2}$$

The results show that a 1°C increase in temperature raises the range attainment rate by 0.42%, while a 1 km/h increase in speed reduces it by 0.18%. Turning on the air-conditioning system reduces the attainment rate by about 5.2%. Ambient temperature delivers the largest positive contribution among all explanatory variables, which verifies its dominant role in driving range prediction.

5.2. Model evaluation and validation

The coefficient of determination is $R^2 = 0.84$, which means that the model explains 84% of the variation in range attainment. The model fit is therefore acceptable for the purpose of scenario-level prediction. The mean absolute error (MAE) is 2.3%, and the maximum error is 4.8%, both within an acceptable range. Residual analysis shows that the residuals are distributed relatively evenly, with no clear systematic trend. This supports the rationality and stability of the model.

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6. Discussion

Using the established model, range attainment was predicted under four typical operating scenarios, as shown in Table 3.

Table 3. Range prediction under typical scenarios

Scenario	Temperature	Speed	Predicted attainment rate	Actual range
Winter commute	-5°C	40 km/h	74.5%	373 km
Summer highway driving	30°C	110 km/h	78.2%	430 km
Spring/autumn urban driving	20°C	35 km/h	95.2%	400 km
Winter highway driving	-10°C	120 km/h	62.8%	377 km

The prediction results show a clear difference between the tested scenarios. The range achievement rate hits its minimum of 62.8% under winter highway conditions and reaches a maximum of 95.2% in urban driving during spring and autumn. This is consistent with common user experience: low temperature and high-speed driving usually lead to the largest range loss, while mild weather and urban speeds are more favorable for electric vehicles. The model was further used to compare the range performance of different vehicle models. Among the tested models, the BYD Dolphin achieves the highest range achievement rate at 90.5%, attributed to its Blade Battery and comprehensive energy management system. The NIO ET5 follows with an attainment rate of 88.4%, partly supported by its thermal-management system and battery-swapping design. The Tesla Model 3 shows higher energy consumption in highway driving, with an overall attainment rate of about 80%. These differences suggest that real-world range is not determined by battery capacity alone, but also by battery technology, thermal-management design, aerodynamic performance, and whole-vehicle energy control.

7. Conclusion

Based on on-road driving data, this study adopts multiple linear regression to explore the core factors influencing driving range achievement of new energy vehicles.

Sensitivity of influencing factors: The results show that ambient temperature is the most important factor influencing range loss, accounting for nearly 40% of the variation. Under low-temperature conditions, diminished electrochemical activity of traction batteries and increased load on thermal management systems jointly cut down the effective driving range. This combined effect explains why electric vehicles often show a clear range drop in winter.

Prediction accuracy and model stability: These outcomes indicate that the model delivers reliable driving range predictions across diverse driving scenarios and features low computational complexity. These results suggest that the model can provide useful range estimates under different driving conditions while keeping the calculation relatively simple.

Validity of the modeling method: The study shows that linear regression remains useful for range prediction when sample sizes are limited and the main variables are clearly defined. It offers a feasible solution to convert fragmented on-road test data into a standardized prediction model.

This study still has some limitations. The adopted linear model fails to fully capture nonlinear interference factors, including aggressive driving acceleration, road gradient fluctuations and real-time traffic status. The sample also covers only a limited number of vehicle models, so broader cross-brand data are needed. Future work could test methods such as gradient boosting decision

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trees (GBDT) or deep neural networks to model interactions among variables more accurately and further reduce prediction error.

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