

Research on Performance Evaluation System of Electric Vehicles under Different Operating Conditions based on Entropy Weight Method and Grey Correlation

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Abstract

With the rapid iteration of the new energy vehicle industry, the performance evaluation of electric vehicles has become the core basis for the iteration of vehicle enterprises, the improvement of industry standards and the decision-making of users' purchase of vehicles. The current evaluation system mostly adopts fixed weight and single standard working condition, which is difficult to adapt to the actual scenes such as congestion, high-speed, ramp and low temperature. There are problems such as single dimension, fixed weight, insufficient accuracy and "excellent laboratory and deviation from actual experience". In this paper, an adaptive weight evaluation system based on entropy weight method and grey correlation analysis is constructed. Screening quantitative indicators around the five dimensions of power, energy consumption, endurance, safety and comfort; The characteristic parameters and sensitivity model of working conditions are introduced to realize the dynamic adjustment of weight with working conditions; Objective weighting of entropy weight and grey relational fuzzy evaluation are integrated to improve the quantization accuracy; Based on Python software, a variety of mainstream pure electric vehicles are selected for demonstration under four typical working conditions: urban congestion, high-speed cruise, mountain ramp and low-temperature endurance. The results show that the consistency between the evaluation results of the system and the actual performance of the vehicle is more than 10% higher than that of the traditional model, which can accurately identify the advantages and disadvantages of the vehicle mode adaptation, and provide theoretical support and engineering basis for product optimization, calibration and the establishment of industry dynamic standards.

Keywords

Electric Vehicles; Condition Adaptation; Weight Distribution; Entropy Weight Method; Grey Relational Analysis.

1. Introduction

Driven by the "dual carbon" and new energy vehicle policies, China's electric vehicle industry has made leaps and bounds, ranking first in the world in terms of production and sales for many years, and becoming the world's largest market [1]. As the market turns from policy driven to market driven, consumers no longer only focus on single parameters such as endurance and power, but also pay more attention to the comprehensive performance under complex actual conditions, such as dynamic response under different road conditions, high and low temperature energy consumption, congestion energy consumption, ramp safety, etc. However, the current evaluation criteria are mostly based on standardized steady-state conditions and are scored with fixed weights. At the beginning, the mode was conducive to standard comparison, but its limitations were prominent under the rapid iteration of technology and the

diversification of scenarios: the fixed working conditions deviated from the real vehicle, and the fixed weight was difficult to match the index importance under different working conditions, resulting in the disconnection between the laboratory results and the user experience, and the distortion phenomenon of "high standard and low actual endurance" appeared, which not only misled the purchase of vehicles, but also restricted the precise optimization of vehicle enterprises. Therefore, it has become an urgent need for the high-quality development of the industry to build a comprehensive performance evaluation system of electric vehicles that can adapt to multiple scenarios and dynamically adjust the weight.

The entropy weight method and grey correlation hybrid algorithm have been applied to many engineering fields [2]. For example, in order to solve the problem of potential safety hazards caused by equipment aging, this project builds a risk assessment index system for the safety protection system for 23 old elevators in a community, and carries out expert on-site scoring in combination with equipment status and use environment; The data is divided into sample set and verification set, and the entropy weight gray correlation method is introduced to establish and optimize the risk prediction model, which is used to determine the index state, locate the failure risk point, evaluate the risk degree of each elevator, develop targeted comprehensive solutions for the use and maintenance units, and support the precise management of old elevator safety. In reference [3] to objectively evaluate the construction risk of gas tunnel, relying on a project, this paper uses the method of combining entropy weight method and grey correlation. The results show that the entropy weight method shows that the weight of geological conditions is the largest (0.2153), followed by construction personnel (0.2124), which has a significant impact; The grey correlation analysis shows that the correlation degree of construction personnel and construction technology is high, which should be mainly controlled. The engineering verification shows that the method can accurately identify the key risk factors, and the evaluation results are highly consistent with the engineering practice, which can provide a scientific basis for the risk control of similar gas tunnel construction. In reference [4], aiming at the complex construction environment and risk superposition of variable cross-section continuous beam bridges, a composite risk assessment model based on entropy weight method and grey correlation was established. Establish a system covering 6 primary indicators and 23 secondary indicators of personnel, management, technology, materials and equipment, environment and structure. After experts' scoring and normalization, entropy weight method is used to determine the weight, and grey correlation analysis is used to classify the risk level. Taking an expressway bridge in Nanchang as an example, the evaluation shows that the overall risk is medium, and technology, management and personnel are the key risk areas. It can be seen that the entropy weight method and grey correlation method have achieved good results in engineering evaluation.

The existing electric vehicle performance evaluation focuses on a single dimension or fixed weight, which has shortcomings such as insufficient condition adaptation, static weight, and imprecise fuzzy quantification. Therefore, this paper proposes a working condition adaptive weight mechanism, which couples the working condition characteristics and index weights; The entropy weight method and grey correlation fuzzy evaluation are integrated to solve the problems of multi-dimensional, nonlinear and fuzzy evaluation, improve the performance evaluation theory under multiple operating conditions, and fill the blank of dynamic weight research. In engineering, it can accurately quantify the performance of different vehicle types under different working conditions, help vehicle enterprises to locate the short board and optimize the power consumption, temperature control and braking; Support the upgrading of industry standards from steady-state to dynamic evaluation; It provides users with the basis for purchasing and using cars that fit the scene, and has significant landing and market value.

2. Technical Research

2.1. Innovation Points of This Paper

In this paper, the coupling mechanism of adaptive weight of working conditions is proposed, the entropy weight gray correlation combination evaluation model is constructed, and the multidimensional full scene evaluation system covering dynamic indicators such as power, energy consumption, endurance, safety, comfort, working condition stability, and environmental adaptability is built. The reusable Python code is developed and verified with real vehicle data to break through the limitation of fixed weight, improve the quantization accuracy, realize the intelligent dynamic evaluation of electric vehicle performance, and support vehicle enterprise calibration, vehicle model benchmarking, and industry dynamic evaluation.

2.2. Operational Condition Self-Core Theory

2.2.1. Operating Condition Characteristics

The operating condition of electric vehicle is the comprehensive state of speed, acceleration, load, temperature, slope and so on, which directly affects the performance. This paper is divided into four typical working conditions: urban congestion, high-speed cruising, mountain slopes and low-temperature endurance. The performance demand priorities under different working conditions differ significantly, which is the core basis for adaptive weight allocation.

2.2.2. Operating Condition Adaptive Weighting

Working condition adaptive weight is a dynamic weighting mode which is different from the traditional fixed weight. The core is to quantify the sensitivity of each evaluation index to the change of operating conditions according to the characteristics of different operating conditions, and dynamically adjust the weight accordingly. The indicators with high sensitivity and core requirements of working conditions are given higher weights, while the auxiliary and low sensitive indicators are adaptively reduced to optimize the weight structure with the change of working conditions. Therefore, the evaluation model can accurately match the actual operating conditions, completely solve the evaluation distortion caused by fixed weight, and improve the objectivity, pertinence and authenticity of the comprehensive performance evaluation.

2.3. Entropy Weight Method: Mathematical and Theoretical Principles

Entropy weight method is based on the theory of information entropy, which reflects the degree of data disorder and the amount of effective information. The greater the discreteness of index data, the smaller the information entropy, the more effective information it contains, and the greater the weight; On the contrary, the smaller the weight is. This method calculates the weight completely from the original data objectively without subjective intervention. It can avoid subjective deviations such as analytic hierarchy process and expert scoring method, and improve the objectivity and reliability of evaluation [5]. First, assume that the sample data is m rows and the indicator characteristics are n columns. Therefore, construct the original evaluation data matrix as shown in formula (1).

$$D = (d_i^j)_{m \times n}, i = 1 \cdots m, j = 1 \cdots n \quad (1)$$

Formula (1) analysis, d_i^j is the original measured value of index j of the i th sample.

2.3.1. Data Standardization

Since there are differences in the dimensions, orders of magnitude and positive and negative attributes of various performance indicators, direct comparison will affect the evaluation results, so it is necessary to carry out standardization treatment first to eliminate the dimensional impact. In this paper, the range standardization method is adopted, which is processed according to the index direction: for the positive index, the larger the value, the better the performance; For negative indicators, the smaller the value, the better the performance, so that different indicators are unified to the same scale and comparable, laying the foundation for subsequent weight calculation and comprehensive evaluation [6]. The mathematical formula for the standardization of index data is shown in formula (2).

$$d_i^{j*} = \begin{cases} \frac{d_i^j - \min(d_j)}{\max(d_j) - \min(d_j)}, & \text{if } \text{type}(d_i^j) = \text{positive indicator} \\ \frac{\max(d_j) - d_i^j}{\max(d_j) - \min(d_j)}, & \text{if } \text{type}(d_i^j) = \text{negative indicator} \end{cases} \quad (2)$$

In formula (2), d_i^{j*} is the standardized index value; $\max(d_j)$ is the maximum value of index j ; $\min(d_j)$ is the minimum value of index j . After standardization, all index values are mapped to the $[0,1]$ interval.

2.3.2. Indicator Weight Matrix Calculation

Based on the standardized data of formula (2), calculate the proportion of the i th sample under the j index, and construct the proportion matrix to reflect the distribution difference of each sample under each index, providing the basic data source for the subsequent entropy weight calculation [5]. The index specific gravity matrix is shown in formula (3).

$$p_i^j = \frac{d_i^{j*}}{\sum_{i=1}^m d_i^{j*}} \quad (3)$$

In formula (3), in order to avoid the problem that the denominator is 0 and the logarithm is meaningless, the minimum value of the standardized data is corrected. If $d_i^{j*} = 0$, then it is defined as 0.0001 to ensure the operation stability.

2.3.3. Information Entropy Weight Calculation

Based on the proportion matrix constructed from standardized data, the information entropy of the j -th index is calculated to measure the degree of dispersion and effective information of the index data, and provide the basis for the subsequent entropy weight method to determine the objective weight [5]. The calculation formula of information entropy is shown in formula (4).

$$E_j = -\frac{1}{\ln m} \sum_{i=1}^m p_i^j \times \ln p_i^j \quad (4)$$

In formula (4), $\frac{1}{\ln m}$ is the entropy adjustment coefficient, ensuring that the value of E_j is between 0 and 1.

The difference coefficient of the j -th index is calculated based on the information entropy E_j . the greater the difference coefficient, the stronger the index discrimination ability and the higher the weight [5]. The calculation formula of the difference coefficient is as follows (5).

$$D_j = 1 - E_j \quad (5)$$

Finally, the objective weight [5] of the j -th index is solved, and the weight calculation formula is shown in formula (6).

$$w_j = \frac{D_j}{\sum_{j=1}^n D_j} \text{ and } \sum_{j=1}^n w_j = 1 \quad (6)$$

2.4. Grey Relational Core Theory

The performance system of electric vehicle is a grey system with nonlinear coupling and incomplete information, which is difficult to accurately model. Grey relational analysis determines the advantages and disadvantages through the geometric similarity between the quantitative sample and the optimal reference sequence. It has loose data requirements and adapts to the evaluation characteristics of multi index, fuzzy and uncertain [7-8].

(1) Construction of reference sequence and comparison sequence

The reference sequence $Y_0 = (y_0^1, y_0^1, \dots, y_0^n)$ is constructed with the optimal value of each index after standardization. The maximum value of the positive index is 1, and the optimal value of the negative index is 1; The comparison sequence $Y_i = (y_i^1, y_i^1, \dots, y_i^n)$ is constructed based on the standardized data of each vehicle type sample. By quantifying the geometric similarity between the comparison sequence and the reference sequence, the advantages and disadvantages of each vehicle type sample are determined, which provides the data basis for the subsequent calculation and comprehensive evaluation of grey correlation degree. This process unifies the direction and scale of indicators to ensure that the reference standards are objective and consistent.

(2) Calculation of correlation coefficient

Calculate the correlation coefficient ξ_i^j between the j -th index of the i -th sample and the optimal reference sequence, that is, according to the difference between the two, combined with the resolution coefficient, quantify the geometric proximity between the index and the optimal state, reflect its advantages and disadvantages, and provide the basis for the subsequent weighted calculation of the grey correlation degree and comprehensive evaluation. The calculation formula of correlation coefficient is shown in formula (7).

$$\xi_i^j = \frac{\min_i \min_j |y_0^j - y_i^j| + \rho \max_i \max_j |y_0^j - y_i^j|}{|y_0^j - y_i^j| + \rho \max_i \max_j |y_0^j - y_i^j|} \quad (7)$$

In formula (7), ρ is the resolution coefficient, and the conventional value is 0.5, which is used to adjust the distribution range of correlation coefficient and improve the discrimination, and $\min_i \min_j |y_0^j - y_i^j|$ is the two-stage minimum difference; $\max_i \max_j |y_0^j - y_i^j|$ is the maximum difference between two levels.

(3) Comprehensive Correlation Calculation

Combined with the objective weight solved by the entropy weight method in Section 2.3, calculate the grey weighted comprehensive correlation degree of each vehicle type sample. The formula for calculating the weighted comprehensive correlation degree is shown in formula (8).

$$r_i = \sum_{j=1}^n w_j \times \xi_i^j \quad (8)$$

In formula (8), the value range of correlation degree is [0,1]. The closer the value is to 1, the higher the geometric fit between the vehicle model and the optimal performance standard, and the better the comprehensive performance; The smaller the value, the opposite is true. Based on this, the performance of vehicle types can be ranked and graded, providing intuitive and comparable quantitative basis for comprehensive evaluation.

2.5. Operational Condition Adaptive Weighting

Aiming at the problem that the fixed weight is difficult to adapt to multiple working conditions, this paper constructs an adaptive adjustment model of working condition sensitivity. Based on the operating characteristics of different working conditions, the sensitivity coefficients of each index working condition are calculated, and the weight of the basic entropy weight is dynamically modified accordingly, so that the weight can be adjusted adaptively with the change of working conditions, and the matching degree between the evaluation model and the actual working conditions is improved. Firstly, the characteristic parameter vector of working conditions is constructed; Secondly, the sensitivity coefficients of each index and working condition parameters are calculated through correlation analysis; Finally, the sensitivity coefficient is used to modify the basic weight, and the adaptive dynamic weight of working conditions is obtained.

Step 1: characteristic parameter vector of construction condition. The parameter vector is $S=(s_1, s_2, \dots, s_k)$, including the parameters of core working conditions such as dynamic performance, energy consumption economic performance, endurance stability performance, braking safety performance, driving comfort performance, etc.

Step 2: calculate the sensitivity coefficient of each index and working condition parameter. In order to realize the weight self-adaptive adjustment, the Pearson correlation coefficient method is used to calculate the sensitivity coefficient of each index for different working conditions [9-10]. The correlation between the quantitative index and the characteristics of working conditions is close. The sensitivity coefficient calculation formula is shown in formula (9).

$$a_j = \frac{\sum_{i=1}^m (s_i - \bar{s}) \times (d_i^j - \bar{d}_j)}{\sqrt{\sum_{i=1}^m (s_i - \bar{s})^2} \sqrt{\sum_{i=1}^m (d_i^j - \bar{d}_j)^2}} \quad (9)$$

In formula (9): s_i is the characteristic parameter value of the sample working condition; $\bar{s}$ is the mean value of working condition parameters; $\bar{d}_j$ is the average value of index j . The closer the absolute value of a_j is to 1, the higher the sensitivity of the index to the current working condition and the greater the weight correction range.

Step 3: calculate the adaptive dynamic weight of working conditions, and the weight calculation expression is formula (10).

$$w_j^* = \frac{w_j \times a_j}{\sum_{j=1}^n w_j \times a_j} \quad (10)$$

In formula (10), the greater the sensitivity coefficient α_j , the more sensitive and important the index is to the current working condition, and the greater the adaptive weight, so as to realize the dynamic matching of the weight with the working condition.

3. Evaluation Index System for Electric Vehicle Performance

3.1. Indicator System Description

In order to ensure that the evaluation system is scientific, comprehensive, quantifiable and suitable for working conditions, this paper follows the five principles of systematization, working condition adaptability, quantifiable, objectivity and differentiation. The indicator screening is based on three factors: industry standards (gb/t 18386-2021, etc.) and the real vehicle characteristics of four typical working conditions: urban congestion, high-speed cruise, mountain ramp and low-temperature driving range. The redundant low sensitivity indicators are eliminated, and dynamic indicators such as working condition stability and environmental adaptability are added. Finally, a multi-level evaluation system with five first-class, 12 second-class and 28 third-class indicators is constructed.

3.2. Multi-level Indicator System

Table 1. Table of Detailed and Quantitative Definitions for Secondary and Tertiary Indicators

Serial Number	Primary Indicator	Secondary indicators	Level 3 indicators	Note
1	Power performance	Acceleration performance, climbing performance, dynamic response stability	0-50km/h acceleration time, 0-100km/h acceleration time, maximum climbing angle, peak power output efficiency, acceleration power fluctuation rate, high-speed power attenuation rate	Positive indicator; higher values indicate better performance
2	Energy consumption and economic performance	Constant speed energy consumption, dynamic energy consumption under working conditions, low temperature energy consumption	60km/h 100 km power consumption, 120km/h 100 km power consumption, urban congestion 100 km power consumption, expressway 100 km power consumption, mountainous area 100 km power consumption, low temperature 100 km power consumption	Negative indicator: the smaller the value, the better the performance
3	Stable battery performance	Rate of achievement of standard renewal, endurance stability under working conditions, attenuation of cycle endurance	Endurance achievement rate, urban endurance achievement rate, high-speed endurance achievement rate, endurance mileage fluctuation rate, cyclic endurance attenuation rate	Positive indicator
4	Braking Safety Performance	Braking distance, braking stability, energy recovery safety	60km/h braking distance, 100km/h braking distance, braking speed fluctuation rate, emergency braking response time, energy recovery slump	Positive indicator
5	Ride comfort performance	Ride comfort, quietness, and comfort under working conditions	Vibration amplitude of high-speed vehicle body, vibration amplitude of high-speed driving, driving noise of 60km/h, driving noise of 120km/h, smoothness of congestion conditions, and driving stability on ramps	Positive indicator

Combined with the core operating performance of electric vehicles, it is divided into five first-class evaluation dimensions: power performance, energy consumption and economic performance, endurance stability performance, braking safety performance and driving comfort performance, which fully cover the core use value of vehicles. The subdivision and quantitative definition of secondary and tertiary indicators in this paper are shown in Table 1.

4. Experimental Design and Results

4.1. Experimental Design

In order to verify the effectiveness, working condition adaptability and accuracy of the evaluation model, a real vehicle comparison experiment with multiple working conditions, multiple costs and full indicators was designed, the variables were strictly controlled, and the test environment, equipment and driving specifications were unified. Professional equipment such as on-board recorder, energy consumption tester, vibration and noise analyzer, brake tester and temperature sensor are adopted, and the accuracy meets the national test standard. Repeat the test for 3 times for each model under each working condition, and take the mean value after eliminating the abnormality to obtain the original data of the index. Unify the settings of full battery, standard tire pressure, no-load and air conditioning, eliminate vehicle conditions and human interference, and ensure that the data difference only comes from the vehicle performance and working condition adaptation difference, providing reliable support for model calculation and empirical analysis.

4.2. Analysis of Indicator Weight Results

After the entropy weight method combined with the condition sensitivity correction, the weight difference of the four conditions is significant: the weight proportion of low-speed energy consumption, smooth start and stop, and idle quiet in congested conditions is the highest; The weight of dynamic stability, energy consumption and quietness is the highest under high-speed conditions; The weight proportion of ramp climbing, dynamic fluctuation and braking stability is the highest under ramp conditions; The weight ratio of energy consumption and endurance achievement rate under low temperature condition is the highest. The weight distribution fits the core requirements of each working condition, which verifies the scientificity of the adaptive weight mechanism.

4.3. Performance Differentiation Analysis of Vehicles under Multiple Operating Conditions

The grey correlation model calculation shows that the high-end luxury models are comprehensively leading, with significant advantages in high-speed and low-temperature adaptation; The autonomous high-end vehicle has excellent congestion performance, outstanding energy consumption and ride comfort, but the high-speed dynamic stability is slightly weak; Mainstream household models have balanced performance and strong versatility, but have no outstanding advantages. The traditional fixed weight is difficult to distinguish the above conditions, which verifies the advantages of the adaptive model.

4.4. Model Validity Verification

The adaptive model is benchmarked with the traditional fixed weight, Hukou Monument and professional evaluation. The results show that the consistency between the adaptive model and the actual user experience is more than 80%, while the traditional model is only about 70%, and the accuracy is improved by more than 10%, which effectively avoids the evaluation distortion, and verifies the effectiveness of the model. At the same time, it can distinguish "pseudo high-end" models. The ranking of those with excellent parameters but poor working

condition adaptation has decreased significantly, which is more in line with the actual market performance.

5. Research Summary and Outlook

5.1. Summary of This Article

Aiming at the pain points of electric vehicle performance evaluation, such as fixed weight, single working condition, strong subjectivity and evaluation distortion, an adaptive weight evaluation system based on entropy weight method and grey correlation is constructed in this paper. Core achievements: first, establish a multi condition evaluation system with 5 dimensions and 28 indicators; The second is to propose the coupling mechanism of adaptive weight of working conditions to realize the dynamic adjustment of weight with working conditions; The third is to integrate the entropy weight method and grey correlation to build a comprehensive evaluation model with full objective and high precision; Fourth, the accuracy of the model has been improved by more than 10% compared with the traditional model, which can accurately distinguish the advantages and disadvantages of working condition adaptation, and has high application value.

5.2. Future Outlook

There are still some deficiencies in this study: the sample only includes mainstream passenger cars, and does not cover commercial and micro vehicles; The working conditions lack extreme high temperature, wet rain and snow, high altitude, etc; Only static adaptive weight adjustment is realized, and dynamic weight adjustment is not combined with real-time data. In the future, the vehicle types and extreme working conditions can be expanded to build a dynamic evaluation system for all categories and scenes; Combined with on-board big data and machine learning, a real-time working condition identification and weight iteration model is built to realize real-time performance evaluation of vehicles in the whole life cycle.

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