Residual Value Evaluation of Operating Pure Electric Vehicles Based on Machine Learning

Yujui Wang¹,²,³, Maohua Huang¹,²,³,* and Kailun Chen¹,²,³

¹Hubei Key Laboratory of Advanced Technology for Automotive Components, Wuhan University of Technology, Wuhan 430070, China
²Hubei Key Laboratory of Advanced Technology for Automotive Components, Wuhan University of Technology, Wuhan 430070, China
³Hubei Research Center for New Energy & Intelligent Connected Vehicle, Wuhan University of Technology, Wuhan 430070, China

*e-mail: wyj1126@whut.edu.cn
*Corresponding author: *e-mail: mh_huang@163.com

Abstract: In view of the current imperfect second-hand evaluation system for new energy vehicles, there are limitations such as simple evaluation models, strong subjectivity, and large evaluation differences. This paper establishes the residual value evaluation model for operating pure electric vehicles, combining actual vehicle operation and maintenance data and establishes the residual value rate evaluation model based on the XGBoost algorithm and Boosted Trees enhanced algorithm. The multi-dimensional feature data of vehicle type, service time, mileage and region are extracted by feature engineering, and the evaluation system of residual value rate correction coefficient is established based on AHP. Finally, based on residual value rate evaluation model and the residual value rate correction coefficient system model to optimize the replacement cost method evaluation model, thereby constructing a complete residual value evaluation model. The model is based on actual vehicle operating data and machine learning algorithms, which has strong pertinence and real-time for the residual value evaluation of pure electric vehicles.

1. Introduction

With the popularization and development of new energy vehicles, the proportion of pure electric vehicles in the operational travel vehicles is increasing. However, due to the new energy used car trading market system has not been formed, the number of new energy used car markets is low. There are some problems in the residual value evaluation of pure electric vehicles, such as the lack of detection methods, the rapid technology upgrading, the large difference of value preservation rate and the difficulty of valuation. At present, the second-hand vehicle detection and evaluation methods mainly focus on the evaluation of fuel vehicles, including the current market price method, income present value method, liquidation price method and replacement cost method [1]. The existing evaluation methods have the limitations of simple modelling and strong subjectivity, which cannot be fully applied to new energy electric vehicles. Therefore, it is necessary to establish an evaluation model for the residual value of operating pure electric vehicles.
2. Residual value evaluation model
The model takes the replacement cost method as the basic evaluation method, and optimizes the replacement cost method model [2]. The model includes the evaluation of vehicle residual value rate based on machine learning method, the establishment of residual value rate correction coefficient evaluation system from the physical depreciation, economic depreciation and functional depreciation [3] and the evaluation of vehicle replacement cost based on real vehicle data, thereby establishing the evaluation model of vehicle residual value. The evaluation process of residual value model is shown in Figure 1.

Figure 1. Residual value evaluation process

2.1. Evaluation model of residual value rate
Based on XGBoost algorithm and Boosted Trees enhancement algorithm in machine learning, the residual rate evaluation model is established. The process framework of the model is shown in Figure 2. Vehicle operation and maintenance data is used as the dataset of the model. First, the dataset is pre-processed to eliminate abnormal data, and then feature engineering is established to standardize the data and extract features. The vehicle type, operation time, mileage, region and second-hand vehicle valuation are selected as the feature data from the dataset.

The feature dataset is expressed as follows:

\[ T = \{(x_i, y_i) \} \ (|T| = n, \ x_i \in \mathbb{R}^m, \ y_i \in \mathbb{R}) \]

Where \( x_i \) is the sample, \( m \) is the sample characteristics: vehicle type, mileage, time, region, second-hand vehicle valuation, \( y_i \) is the sample label: vehicle residual value rate.

XGBoost algorithm and Boosted Trees enhancement algorithm are used to train the feature data [4], and the prediction function as shown in equation (1) and loss function as shown in equation (2) of the vehicle residual value evaluation model are established. After evaluating and optimizing model, the vehicle residual value rate evaluation model is output. By inputting the data of the vehicles to be evaluated into the residual value rate evaluation model, the residual value rate of the vehicles to be evaluated can be obtained. The input data of vehicles to be evaluated include vehicle type, mileage, time and region.

\[ \hat{y}_i = \sum_{k=1}^{K} f_k(x_i), f_k \in F \]  
\[ Obj^{(t)} = \sum_{i=1}^{n} \left[ 2(\hat{y}_i^{(t-1)} - y_i) + f_i(x_i)^2 \right] + \Omega(f_i) + C \]  

(1)  
(2)
Where $\hat{y}_i$ represents the prediction result of the sample $x_i$, that is, the estimated vehicle residual value rate, $K$ is the total number of model trees, $F$ represents all the function spaces in the regression forest, and $f_k(x_i)$ represents the weight of the leaves in the tree of the sample.

2.2. Evaluation system of correction coefficient of residual value rate

The residual value rate correction coefficient evaluation system takes the vehicle's physical depreciation, economic depreciation and functional depreciation as correction parameters, including vehicle condition, maintenance condition, working environment, power battery, after-sales service level, brand value preservation rate, vehicle upgrade and price stability. The correction coefficient system of residual value rate is shown in Figure 3. Through the establishment of AHP model, the weight of influencing factors is quantified, and the score system of influencing factors is established, which forms the evaluation system of residual value rate correction coefficient.

Through the AHP model, the weight of the influence parameters of the residual value rate correction coefficient is quantified, and the weight of the influence parameters is shown in Table 1. The AHP model is based on three major factors: physical depreciation, functional depreciation and economic depreciation. The main steps are as follows [5]:

1. Establish the AHP model:
   - Target layer: residual value rate correction coefficient;
   - Standard level: physical depreciation, functional depreciation, and economic depreciation;
   - Solution level: vehicle status, maintenance status, working environment, power battery, model upgrade, price stability, brand retention rate, after-sales service level;
2. Construct judgment matrix;
3. Check the consistency of the judgment matrix;
4. Calculate weight: calculate the weight of the judgment matrix to obtain the weight value of the corresponding factors of the judgment matrix relative to the factors of the upper level.

Figure 2. Evaluation model process framework
Correction coefficient of residual value rate

![Diagram showing the correction coefficient system of residual value rate with branches for Functional depreciation, Physical depreciation, and Economic depreciation, further divided into sub-branches for Vehicle upgrade, Price stability, Vehicle condition, Working environment, Maintenance condition, Power battery, After-sales service level, and Brand value preservation rate.]

Figure 3. Correction coefficient system of residual value rate

| Correction parameters      | Weight  | Influencing factor                      | Weight  |
|---------------------------|---------|-----------------------------------------|---------|
| Physical depreciation     | 61.44%  | Vehicle condition                       | 17.86%  |
|                           |         | Maintenance condition                   | 4.06%   |
|                           |         | Working environment                     | 11.33%  |
|                           |         | Power battery                           | 28.19%  |
| Functional depreciation   | 22.24%  | Vehicle upgrade                         | 16.96%  |
|                           |         | Price stability                          | 5.28%   |
| Economic depreciation     | 16.32%  | Brand value preservation rate            | 12.24%  |
|                           |         | After-sales service level                | 4.08%   |

The vehicle conditions, maintenance condition, working environment, power battery, vehicle upgrade, price stability, brand value preservation rate and after-sales service level parameters are classified, and the scoring coefficient is set for each level to obtain the scoring system model. The scoring system is shown in Table 2.

The parameter characteristics of the vehicle to be evaluated are matched with the parameter characteristics of the scoring system model to obtain the vehicle condition parameter score coefficient $K_1$, maintenance condition parameter score coefficient $K_2$, working environment parameter score coefficient $K_3$, power battery parameter score coefficient $K_4$, model upgrading parameter score coefficient $K_5$, price stability parameter score coefficient $K_6$ and brand value parameter score coefficient $K_7$ and after-sales service level parameter score coefficient $K_8$. Calculate the residual value rate correction coefficient $K$ by equation (3).

$$ K = \sum_{n=1}^{8} p_n K_n $$

Where $K_n$ is the scoring coefficient of each factor and $P_n$ is the weight of each factor.

| Influencing factor       | Level grading | Level description                                                                 | Scoring coefficient |
|--------------------------|---------------|----------------------------------------------------------------------------------|---------------------|
| Vehicle condition        | Good          | No defects, clean interior, normal power system and mechanical parts, no maintenance, etc | 0.9                 |
|                          | Medium        | There are slight defects, a small amount of wear and tear of parts, normal maintenance of mechanical parts, etc | 0.7                 |
|                          | Poor          | There are obvious defects, serious wear of parts, abnormal                         | 0.5                 |
### 2.3. Optimization of replacement cost model

By obtaining the purchase data of the evaluation vehicle to calculate the replacement cost of the vehicle. According to the data provided by the buyer and the vehicle manufacturer, the replacement cost of the vehicle is evaluated according to equation (4).

The model takes the optimized replacement cost method as the basic evaluation method, evaluates the residual value rate and the residual value rate correction coefficient of the vehicle through the residual value rate evaluation model and the residual value rate correction coefficient system, and obtains the residual value of the evaluated vehicle by equation (5).

\[
P_0 = P_0' + P_1' + P_2'
\]

\[
P = P_0 \times C \times K
\]

Where \(P\) is the residual value of the evaluated vehicle, \(P_0\) is the replacement cost of the evaluated vehicle, \(P_0'\) is the purchase price, \(P_1'\) is tax, \(P_2'\) is the license fee, \(C\) is the residual value rate of the evaluated vehicle, and \(K\) is the correction factor of the residual value rate.

### 3. Conclusions

In view of the shortcomings of the current pure electric vehicle residual value evaluation method, this paper proposes the residual value evaluation model for the operation of pure electric vehicles. Based on the actual operation and maintenance data, the model takes the replacement cost method as the basic evaluation method, establishes the machine learning model to evaluate the residual value rate of vehicles, and comprehensively considers the factors of time, mileage, vehicle type and region. In addition, the correction coefficient of residual value rate is added in the model, and the AHP model is established to quantify the weight coefficient of the influencing factors of residual value, so as to comprehensively evaluate the vehicle condition, which has strong pertinence and more accurately evaluate the residual value of pure electric vehicles.
Acknowledgments
This research was sponsored by the National Key Technology Support Program of China (Grant No. 2018YFE0105500), Project Name: Interactive Analysis of Key Influencing Factors of the Commercial Model of Pure Electric Vehicle Promotion in Typical Scenarios.

References
[1] Zhou, Y. (2013) Research on the value evaluation method of second-hand car. Communications Science and Technology Heilongjiang, 36(11):172-174.
[2] Li, H.W. (2019) Evaluation of the residual value of pure electric vehicles based on the replacement cost method. Automobile & Parts, 03:61-63
[3] Cao, J.X. (2014) Research on used car performance evaluation model based on Data Mining Technology. Market Modernization, 24:17-18
[4] Shi, P.X. (2017). Evaluation and prediction of used car based on Data Mining. Suzhou University, April, 2017
[5] Lin, Y. L., Chen, R. Z. (2010) Research and discussion on determining the surplus value of second-hand car based on AHP. Shanghai Auto, 12:50-54