

Research Article

Research on Teaching Reform of College Student Training Mode Based on Engineering Project Economic Evaluation of Driving Behavior with Internet of Vehicles Data

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Received 1 November 2021; Revised 3 January 2022; Accepted 12 March 2022; Published 12 April 2022

Academic Editor: Chenxi Huang

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Practice is one of the essential teaching links in application-oriented professional teaching in engineering colleges. Reasonable design of practical teaching mode has an important influence on the development of scientific research activities and training of applied talents. In order to better experience the learning combined college student teaching mode, the analysis and mining based on the Internet of Vehicles data is taken as the research scene. Theoretical research and engineering verification of drivers' driving behavior economy are carried out by using the learning method of theoretical research under the guidance of teachers and engineering practice under the guidance of enterprises. An economic evaluation model and energy saving potential calculation method based on fuzzy analytic hierarchy process are established, and the model is verified and improved in engineering practice. Among them, the analysis of personalized characteristics of driver behavior indicators shows that there are obvious differences in individual preference characteristics, generally manifested as fast acceleration and deceleration, low speed driving, gear mismatch. In addition, some drivers' bad driving behavior has an energy saving potential of up to 4.98%. The results show that the combination of school theory research and enterprise engineering practice has positive effects on the development of students' scientific research and the cultivation of applied talents that contribute to the development of enterprises.

1. Introduction

China Association for Professional Certification of Engineering Education defines an authoritative index of engineering education in colleges and universities, namely the engineering education certification standard. The standard requires students majoring in engineering to complete relevant courses, engineering practice and graduation projects to achieve graduation requirements. This for the school and our students both put forward the theoretical requirements also put forward the practical requirements. Therefore, we should give consideration to both theoretical research and engineering practice in our study and life. In order to better participate in the new model of joint teaching of theoretical research and engineering practice, relevant

research is carried out. The research scenario is based on the analysis and mining of Internet of vehicles data. Theoretical research and engineering verification are carried out on the economic evaluation of drivers' driving behavior by using the learning method of theoretical research under the guidance of teachers and engineering practice under the guidance of enterprises. Firstly, literature research was carried out. Secondly, theoretical research was conducted under the guidance of teachers. Finally, engineering practice and theoretical improvement were carried out with the help of enterprises. The specific research process is described as follows.

In recent years, with the development of transportation and logistics industry, the amount of road cargo transport is increasing, and commercial vehicles are playing an

important role in the transport of goods. By the end of 2019, China will have 10,878,200 trucks. However, commercial vehicles, which account for 10.9% of the total automobile volume, consume much more fuel than passenger vehicles and emit 70% nitrogen oxide (NO_x) and more than 90% particulate matter (PM). It not only brings huge fuel consumption costs [1], but also exerts a serious impact on the atmospheric environment. Therefore, improving the fuel efficiency of vehicles and reducing fuel consumption of vehicles are urgent problems to be solved in the current transportation field. It has an important influence on the vehicle to meet the requirement of “energy saving and emission reduction”.

Many scholars have studied this problem. Among them, improving engine “thermal management” technology [2], improving transmission efficiency [3] and vehicle lightweight research [4] are the main approaches to improve fuel efficiency and reduce fuel consumption in traditional research. With the rise of ecological driving concept, optimizing driving behavior has become another important direction to improve fuel efficiency and reduce fuel consumption. Literature [5] found that in aggressive driving operations, fuel consumption increased by 12%–40%, emissions increased by 20%–50%. Literature [6] indicates that fuel consumption can be significantly reduced by 5% ~ 25% by using energy-saving driving operations. The results show that different driving styles have significant effects on fuel consumption and emissions. Krishnamoorthy and Gopalakrishna [7] studied the method of evaluating the driving ability of truck drivers. Using the data provided by the fleet management system, the influences of driving behavior factors on fuel consumption, such as acceleration at high speed, long idle speed, overspeed, gear speed mismatch and engine noneconomic speed, are analyzed. Frank et al. [8] built an Android application to assist driving behavior. By collecting data related to the car’s CAN bus, the driver CAN obtain a representative ecological score per second. The system can introduce the basic concepts and suggestions of green driving to the driver during driving. Fuel consumption tests conducted by seven volunteers showed that the Android app significantly reduced overall energy consumption. Rolim [9] studied the influence of real-time feedback on ecological driving behavior and the variables affecting fuel consumption. Data analysis by The Lisbon bus operator shows that in the absence of real-time feedback on driving behavior, the number of incidents of bad driving behavior has increased significantly. At the same time, trends in fuel consumption were similar to bad driving behavior. Ferreira et al. [10] studied the impact of driving style on fuel consumption by using the speed, acceleration, engine speed and other parameters collected by car CAN bus and GPS device. To assess the level of driving behavior, divide driving behavior into 5 categories. Hsu [11] established an ecological driving behavior analysis model for driving decision-making through data mining technology in order to improve driving efficiency. Aiming at the influence of driver’s personal behavior and vehicle type on driving efficiency, a new comprehensive driving efficiency index was proposed to evaluate driving behavior. Hoang [12] pointed out that improving the

service level is an inevitable requirement for the sustainable development of urban public transport, and proposed a new model to evaluate the driving behavior of bus drivers through traffic planning. In addition, there are many studies in this field [13–18], which prove the feasibility of eco-driving technology to improve the fuel efficiency of existing vehicles. It provides a theoretical basis for further optimization of driving behavior.

In these studies, although the influence of driving behavior indicators on fuel consumption and its relative influence degree are discussed, there is little research on the preference characteristics and energy saving potential of drivers in many bad driving behaviors. However, the analysis of drivers’ preference characteristics in many bad driving behaviors and the accurate description of their fuel consumption impact have important influence on the formulation of efficient and personalized energy-saving optimization strategies. To sum up, this paper carries out relevant work in view of the deficiencies of existing studies. First of all, based on the data of commercial vehicles connected to the Internet, relevant analysis method is adopted to select the economic indicators of driving behavior that have an impact on fuel consumption, and further carry out quantitative evaluation research on driving behavior economy. Secondly, the personalized characteristics of drivers in many bad driving behaviors are analyzed based on the economic evaluation results. Finally, the driving behavior corresponds to the energy saving potential calculation.

The thesis is briefly summarized as follows. In section 2, the theories used in driving behavior evaluation are introduced. Section 3 discusses the process of driving behavior economy evaluation modeling. Section 4 Test the system through real car data and analyze the test results. Section 5 summarizes the work of the full text, and further analyzes the existing shortcomings and prospects.

2. Theory of Economic Evaluation of Driving Behavior

2.1. Selection of Driving Behavior Indicators. In order to reasonably construct the evaluation system of driving behavior economy, the selected evaluation indexes should be targeted and comprehensive. Studies have shown that there are many driving behavior indicators that have an impact on fuel consumption, and the impact degree of relative fuel consumption varies among different indicators. Literature [19] screened driving behavior evaluation indicators by starting from the duration of driving events and combining with data variables representing driving behavior. Literature [10, 20, 21] explored the influence degree of different driving behavior indicators on fuel consumption based on Naive Bayes method, correlation analysis and other methods, and selected driving behavior indicators based on the relative influence degree. The methods and results of index selection of all literature were summarized, and the indexes were preliminarily selected. In order to further analyze the impact of selected indicators on the target fuel consumption of 100 km, Spearman correlation coefficient method [21] was used to calculate the correlation between preliminarily

selected driving behavior indicators and fuel consumption of 100 km, as shown in equation (1). The rationality of index selection is tested by correlation coefficient. ρ is Spearman correlation coefficient, X_i and Y_i are the index data involved in the calculation. N is the dimension of the data.

$$\rho = \frac{\sum_{i=1}^N (X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^N (X_i - \bar{X})^2 \sum_{i=1}^N (Y_i - \bar{Y})^2}} \quad (1)$$

The calculation results of correlation coefficients are shown in Table 1, where the mean speed, mean speed and fuel consumption of the index engine are less than 0.1. It shows that the correlation between these indexes and 100 km fuel consumption is low and can be ignored. Therefore, after removing these irrelevant indicators, 11 indicators with relatively large correlation are finally selected for economic evaluation. To simplify index variable names, abbreviations are used instead of the original names. The details are as follows: ratio of driving idle speed (DS), the proportion of time spent driving at low velocity (LS), speed standard deviation (VSTD), acceleration time ratio (HA), acceleration mean (AMEAN), engine speed standard deviation (SSTD), deceleration time ratio (LA), acceleration rate of change (AC), large throttle operating time ratio (DY), overspeed time percentage (CS), high speed/low speed ratio (LDHV), average engine speed (SMEAN), and average engine speed (VMEAN).

2.2. Establish Evaluation System

2.2.1. Construction of Driving Behavior Economy Evaluation System. Based on the above selected economic evaluation indexes of driving behavior, analytic hierarchy process (AHP) is applied to subdivide the index levels step by step to establish a ladder system of driving behavior evaluation [22]. The target layer is the driving behavior economy score, and the criterion layer is the index of each level. The first-level index U_i has economic evaluation variables such as engine speed, gearbox output shaft speed, speed and acceleration. The second-level index U_{ij} is the statistic corresponding to the economic evaluation variable. The solution layer is each mileage segment, as shown in Figure 1.

2.2.2. Establish the Relationship between Driving Behavior Indicators and Loss Score. Different drivers operate their vehicles differently, resulting in different fuel consumption and economy scores. Relative to the correct operating mode, the actual operation of each driving economy evaluation index X_i will bring driving efficiency rating score loss value ΔF_i and fuel consumption loss ΔQ_i . This process can be described by equations (2), (3).

Here f_i and q_i are the loss description functions corresponding to the i -level index.

$$\Delta F_i = f_i(X_i), \quad (2)$$

$$\Delta Q_i = q_i(X_i). \quad (3)$$

In addition, it is characterized by uncertainty and fuzziness in the process of judging the comparison between actual driving behavior and correct driving behavior. Therefore, it provides an idea for establishing the actual driving behavior economy evaluation model and energy saving potential analysis.

2.3. Fuzzy Comprehensive Evaluation Algorithm. Based on the process analysis of the influence of driving behavior on fuel consumption and the process analysis of driving behavior evaluation, the paper uses fuzzy comprehensive evaluation algorithm to evaluate driving behavior economy [23]. The theory and process of fuzzy evaluation algorithm are introduced below.

2.3.1. Determine the Set of Evaluation Factors. The evaluation factor set is determined according to the evaluation objective. The factors of establishing the driving behavior economy evaluation system based on AHP are as follows. U is the set containing all evaluation factors, and the set element is the driving behavior evaluation factor.

$$U = \{U_1, U_2, \dots, U_m\}. \quad (4)$$

2.3.2. Establish the Comment Set. The grade is divided, and the comment sets corresponding to different grades are determined. V is the set of all comment levels. The set element is the rating level. Fen is the rating set of the corresponding comment and the element is the subset of the rating.

$$\begin{aligned} V &= \{V_1, V_2, \dots, V_n\}, \\ fen &= \{fen_1, fen_2, \dots, fen_n\}. \end{aligned} \quad (5)$$

2.3.3. Determine the Weight Vector of Evaluation Index. Determine the relative influence degree of evaluation factors on the evaluation target, namely the weight W . Evaluation index weight vector W_{ij} corresponds to the weight of the j second-level evaluation index under the i first-level evaluation index.

$$W = \{w_{11}, w_{12}, w_{13}, w_{21}, w_{22}, w_{23}, w_{24}, w_{31}, w_{41}, w_{42}, w_{43}\}. \quad (6)$$

2.3.4. Construct Fuzzy Relation Matrix. The fuzzy membership function is selected based on the data distribution characteristics of the index, and the selected membership function is used to construct the fuzzy relation matrix. R_{ik} is the membership value corresponding to the i driving behavior economy index at different evaluation levels. R_{ik} is combined into a single-index membership vector R_i , and all the single-index membership vectors are combined into a comprehensive evaluation membership matrix R .

TABLE 1: Driving behavior index and fuel consumption correlation coefficient.

Indicator name abbreviation	Spearman correlation coefficient (ρ)	Correlation ranking
DS	0.303**	1
LS	0.306**	2
VSTD	0.255**	3
HA	0.226**	4
AMEAN	0.205**	5
SSTD	0.195**	6
LA	0.193**	7
AC	0.171**	8
DY	0.155**	9
CS	0.151**	10
LDHV	0.104**	11
SMEAN	0.052*	12
VMEAN	-0.049*	13

**indicates significant correlation at 0.01 level.

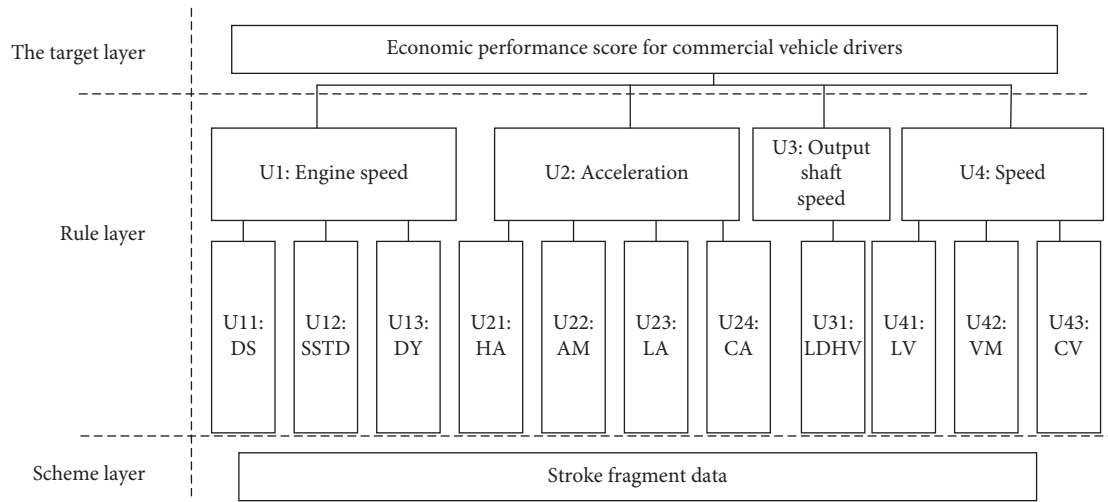


FIGURE 1: Driving behavior economy system evaluation system.

$$R_i = [R_{i1}, R_{i2}, \dots, R_{ik}, \dots, R_{in}],$$

$$R = \begin{bmatrix} R_1 \\ R_2 \\ \cdot \\ \cdot \\ \cdot \\ R_m \end{bmatrix} = \begin{bmatrix} R_{11} & R_{12} & \cdot & \cdot & R_{1n} \\ R_{21} & R_{22} & \cdot & \cdot & R_{2n} \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ R_{m1} & R_{m2} & \cdot & \cdot & R_{mn} \end{bmatrix}. \quad (7)$$

2.3.5. *Fuzzy Calculation.* Through (8), the weight vector obtained and the membership matrix of multi-factor evaluation are fuzzy calculated. S is the obtained fuzzy evaluation result matrix, W is the determined index weight vector, R is the multi-factor evaluation membership matrix determined

by the formula, and the operation symbol is the weighted average fuzzy operator [23]. Formula (9) is used to normalize the fuzzy evaluation result matrix and sum it with the corresponding score segment to get the economic score F .

$$S = W \cdot \oplus R, \quad (8)$$

$$F = \sum_{i=1}^n \frac{S_i}{\sum_{i=1}^n S_i} \times f_i. \quad (9)$$

3. Modeling of Driving Behavior Economy Evaluation System Based on FAHP Algorithm

3.1. *Determine the Set of Evaluation Factors.* According to the hierarchy of driving behavior economy evaluation system in Figure 1, the set of factors is determined as follows, in which

U_{ij} corresponds to the j second-level evaluation index under the first-level evaluation index.

$$U = \{U1, U2, U3, U4\} = \left\{ \begin{array}{c} \{U_{11}, U_{12}, U_{13}\} \\ \{U_{21}, U_{22}, U_{23}, U_{24}\} \\ \{U_{31}\} \\ \{U_{41}, U_{42}, U_{43}, U_{44}\} \end{array} \right\}. \quad (10)$$

3.2. Comment Sets and Corresponding Scores. For each driving behavior indicator, the rating is divided and the corresponding single driving behavior loss assessment set and score set are given. The driving behavior economy score is obtained by comprehensively considering all loss scores, and the corresponding comment set and score set are shown in Tables 2, 3.

3.3. Determine the Weight of Evaluation Index. Different driving behavior indicators have different influences on driving behavior economy score and have different weights. By combining expert experience and 1–9 scale method [22], the judgment matrix showing the relative importance of economic evaluation indexes of driving behavior was given.

$$CI = \frac{\lambda_{\max} - b}{b - 1}, \quad (11)$$

$$CR = \frac{CI}{RI}. \quad (12)$$

In order to further calculate the weight vector, the judgment matrix should meet the requirement of consistency test. The judgment matrix is tested through equations (9) and (10), where CI is the consistency index, RI is the average consistency index, RI values correspond to different judgment matrix orders are shown in Table 4. Lambda Max is the maximum eigenvalue of the judgment matrix, b is the order of the judgment matrix, and CR is the consistency ratio.

The CR value of the judgment matrix is calculated successively, when the consistency ratio $CR < 0.1$, it indicates that the judgment matrix meets the consistency test requirements. If not, the judgment matrix is modified until it meets the requirements. The geometric average method is used to calculate the subjective weight W^a for the judgment matrix meeting the requirements as shown in equation (13), in which A_i is the judgment matrix and the element contained in the judgment matrix is a_{ij} .

$$W_i = \frac{(\prod_{j=1}^b a_{ij})^{1/b}}{\sum_{i=1}^m (\sum_{j=1}^b a_{ij})^{1/b}}, \quad (13)$$

$$W^a = \{W_1, W_2, \dots, W_m\}. \quad (14)$$

Considering the limitation of subjective weighting in analytic hierarchy process (AHP), the objective weighting

TABLE 2: Behavioral loss score set.

Collection of behavior loss comments	Behavior loss score set
Normal loss (I)	(-5,0)
Slight loss (II)	(-40, -5)
General loss (III)	(-60, -40)
A lot of loss (IV)	(-80, -60)
Severe losses (V)	(-100, -80)

TABLE 3: Behavioral evaluation score set.

Behavioral evaluation comment set	Behavior evaluation score set
Poor	(0,20)
Is very poor	(20,40)
Generally poor	(40,60)
Slightly less	(60,95)
Good	(95,100)

TABLE 4: Mean consistency test RI values.

Judge the order of the matrix(b)	1	2	3	4	5	6	7
RI values	0.00	0.00	0.58	0.9	1.12	1.24	1.32

method combined with correlation coefficient is used to improve subjective weighting. The correlation coefficient calculated by formula (1) reflects the objective characteristics of index data and fuel consumption, which can be used as the objective weight basis. The objective weight vector Wb is obtained after normalization. To sum up, the final weight value W is obtained by combining subjective weight and objective weight, as shown in Figure 2. $W_{U_{ij}}$ is the weight value corresponding to the index U_{ij}

3.4. Construct Fuzzy Relation Matrix. To construct the fuzzy relation matrix, it is necessary to select the membership function with the same rule from the existing membership distribution function according to the characteristics of variables to characterize the fuzziness [24]. Data based on index variables have two characteristics: continuity and different influence degree of variable indexes on economic performance score. Different membership functions and membership parameters are used respectively. For the indexes that have great influence on economic evaluation, the fuzzy attribute changes sharply near the cut-off point of membership interval, so it is suitable to choose K parabolic membership function to describe this characteristic. Compare the relative weight vectors of the above driving behavior economy indicators, among which the indicators with larger weight are: idle time ratio, large throttle ratio, standard deviation of engine speed, and low speed driving ratio. Therefore, k-order parabolic type is selected as the membership function to describe the fuzziness. The fuzzy attributes of other variables change gently near the cut-off point, so it is appropriate to select the membership function as ridge function.

The expression of the membership function of the parabolic type of K is shown in equations (15)–(17), which

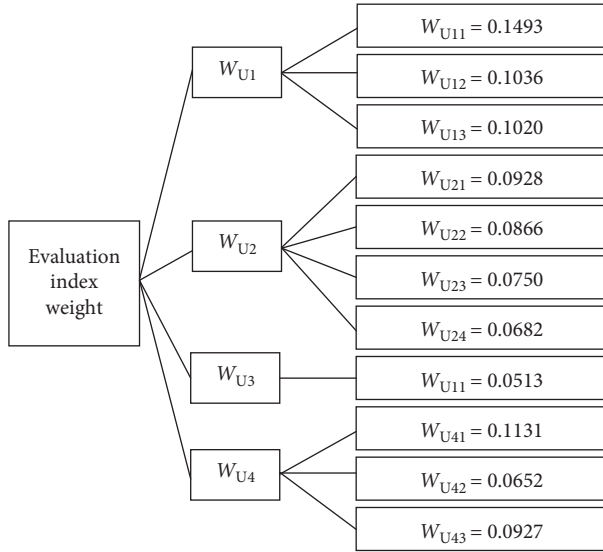


FIGURE 2: Index weight vector allocation.

are, in turn, relatively small, medium and large. Y is the corresponding membership value of each grade. X represents the index data, and X_i represents the threshold value of the index.

$$Y = \begin{cases} 1, & t < x_1, \\ \left(\frac{(x_2 - t)^2}{x_2 - x_1} \right)^2, & x_1 \leq t \leq x_2, \\ 0, & t \geq x_2, \end{cases} \quad (15)$$

$$Y = \begin{cases} 0, & t \leq x_1, \\ \left(\frac{(t - x_1)^2}{x_2 - x_1} \right)^2, & x_1 < t < x_2, \\ 1, & x_2 \leq t \leq x_3, \\ \left(\frac{(x_4 - t)^2}{x_4 - x_3} \right)^2, & x_3 < t < x_4, \\ 0, & t \geq x_4, \end{cases} \quad (16)$$

$$Y = \begin{cases} 0, & t \leq x_3, \\ \left(\frac{(t - x_3)^2}{x_4 - x_3} \right)^2, & x_3 < t < x_4, \\ 1, & t \geq x_4. \end{cases} \quad (17)$$

The ridge function expressions are shown in equations (18)–(20), which in turn are relatively small, intermediate and large.

$$Y = \begin{cases} 1, & t \leq x_1, \\ \frac{1}{2} - \frac{1}{2} \sin \frac{\pi}{x_2 - x_1} \left(t - \frac{x_1 + x_2}{2} \right), & x_1 < t < x_2, \\ 0, & t \geq x_2, \end{cases} \quad (18)$$

$$Y = \begin{cases} 0, & t \leq x_1, \\ \frac{1}{2} + \frac{1}{2} \sin \frac{\pi}{x_2 - x_1} \left(t - \frac{x_1 + x_2}{2} \right), & x_1 < t < x_2, \\ 1, & x_2 \leq t \leq x_3, \\ \frac{1}{2} - \frac{1}{2} \sin \frac{\pi}{x_4 - x_3} \left(t - \frac{x_4 + x_3}{2} \right), & x_3 < t < x_3, \\ 0, & t \geq x_4, \end{cases} \quad (19)$$

$$Y = \begin{cases} 1, & t \leq x_3, \\ \frac{1}{2} + \frac{1}{2} \sin \frac{\pi}{x_4 - x_3} \left(t - \frac{x_3 + x_4}{2} \right), & x_3 < t < x_4, \\ 0, & t \geq x_4. \end{cases} \quad (20)$$

In order to determine the parameter values of the membership function mentioned above, a statistical analysis of the characteristics was carried out based on a large number of real vehicle transportation data, and the parameters of the membership function obtained are shown in Table 5.

4. Engineering Practice Verification and Result Analysis of Evaluation Model

4.1. Driving Behavior Economy Evaluation Data Processing. The data in this paper comes from a T-box (vehicle-mounted intelligent terminal) that is the data acquisition terminal of commercial vehicles, and the interface is used to read the longitude and latitude, speed and instantaneous fuel consumption of the vehicle, etc. The data that can be uploaded by the acquisition terminal include: data acquisition time, vehicle identification code, ECU speed (km/h), instantaneous fuel consumption (L/100 KM), GPS longitude and latitude, cumulative mileage (KM), engine speed (R/min), engine torque (N·M), etc. A total of 36 vehicles of a freight company were collected within a week of the actual road traffic data.

The evaluation model is tested based on the transportation data of Internet of vehicles. To ensure the uniformity of index calculation, set mileage as the control variable. By dividing each driver's transport data into a uniform 20 KM Micro travel segment: a total of 10037 data segments were obtained by 36 drivers within one week, with a cumulative mileage of 200740 KM. The data processing flow is shown in Figure 3.

TABLE 5: Membership function parameter.

Membership function parameter	x1	x2	x3	x4
U11	0.1058	0.1531	0.1559	0.2032
U12	0.0076	0.0109	0.0111	0.0145
U13	180.71	227.89	249.48	296.66
U21	0.00089	0.0128	0.0131	0.017
U22	0.1377	0.1647	0.1856	0.2127
U23	0.0087	0.0123	0.0127	0.0163
U31	24.925	32.955	35.172	43.202
U41	0.0586	0.0854	0.0867	0.1135
U42	0.0474	0.0678	0.0694	0.0899
U43	0.0435	0.0634	0.0643	0.0843

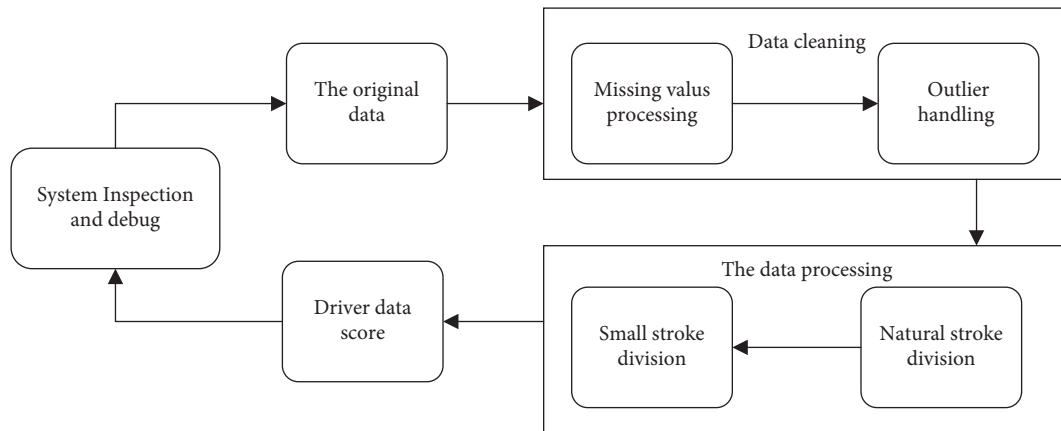


FIGURE 3: Data processing flow chart.

4.2. *Validation of Driving Behavior Economy Evaluation Model and Analysis of Results.* Economic evaluation of driving behavior is conducted within each microstroke segment of the driver, and some representative evaluation results are selected as shown in Figures 4–6. Drivers 5 and 22 represent low frequency of bad driving behavior; drivers 26 and 33 represent medium frequency of bad driving behavior; drivers 3 and 28 represent high frequency of bad driving behavior. The above results indicate that the evaluation system can reflect the difference of drivers’ behavior in different microtravel segments. To further verify the correctness of the evaluation system, check the original index data.

Find the original indicator data based on the low score for verification, as shown in Figure 7. By comparing the reference values of each indicator, it is found that the data of bad driving behavior indicators corresponding to the lower score are more than those exceeding the normal value. This indicates that the evaluation system well reflects the influence of driving behavior on the scoring, and proves the correctness of the evaluation system results.

Further analysis of the results shows that different drivers have different operational performance of bad driving behaviors, as shown in Figure 8. Among them, drivers with serial numbers 2th, 14th, 16th, 29th and 33th all showed a preference for bad driving behaviors with excessive

speed. Therefore, it is necessary to modify the driving habits of these drivers for rapid acceleration.

The drivers with serial numbers 1th, 2th, 11th, 16th, 29th and 33th all have relatively high number of bad driving behaviors, which need to be paid attention to.

In the overall data performance of bad driving behavior, see Figure 9 Different drivers have certain similarities in the performance preference of bad driving behaviors, and the frequency data of bad driving behaviors are further compared. Among them, the indicators with more bad driving behavior frequency are sharp deceleration, low speed, low speed and fast acceleration.

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4.3. *Analysis of Energy Saving Potential.* The driving behavior energy-saving potential of the driver refers to the potential possibility of improving the fuel economy of the vehicle after improving driving behavior. In equations (1) and (2), the relationship between a single driving behavior indicator and

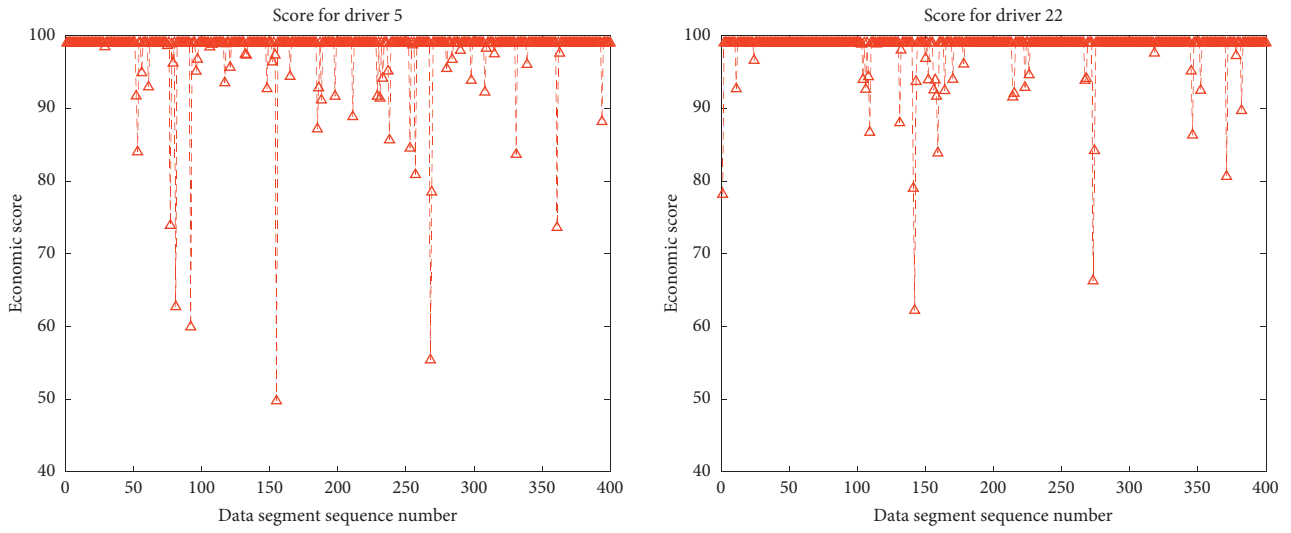


FIGURE 4: Part of the driver's score.

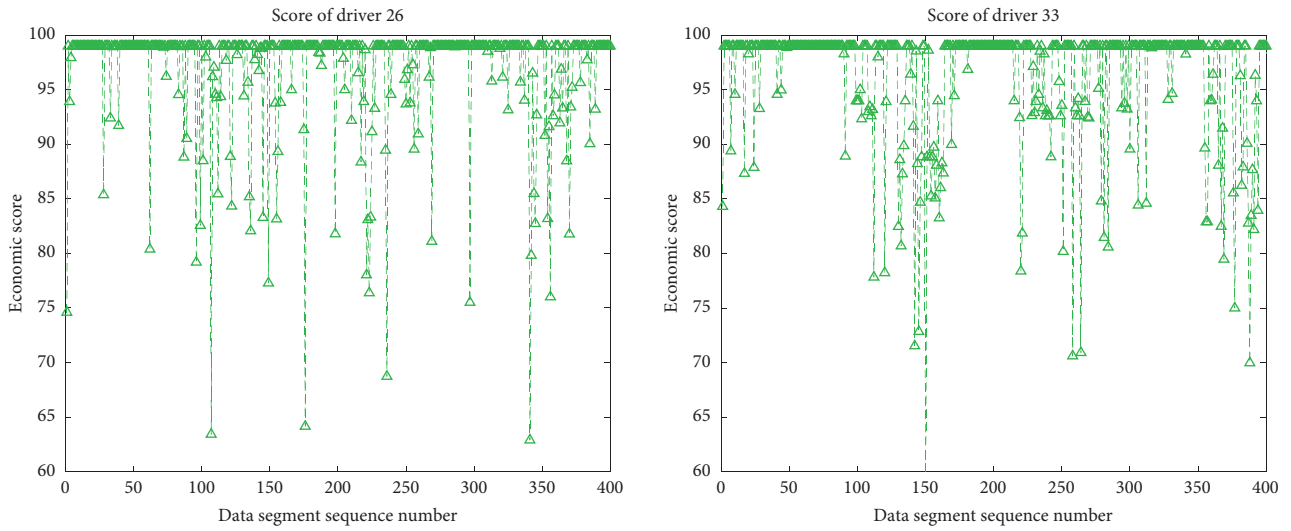


FIGURE 5: Part of the drivers score.

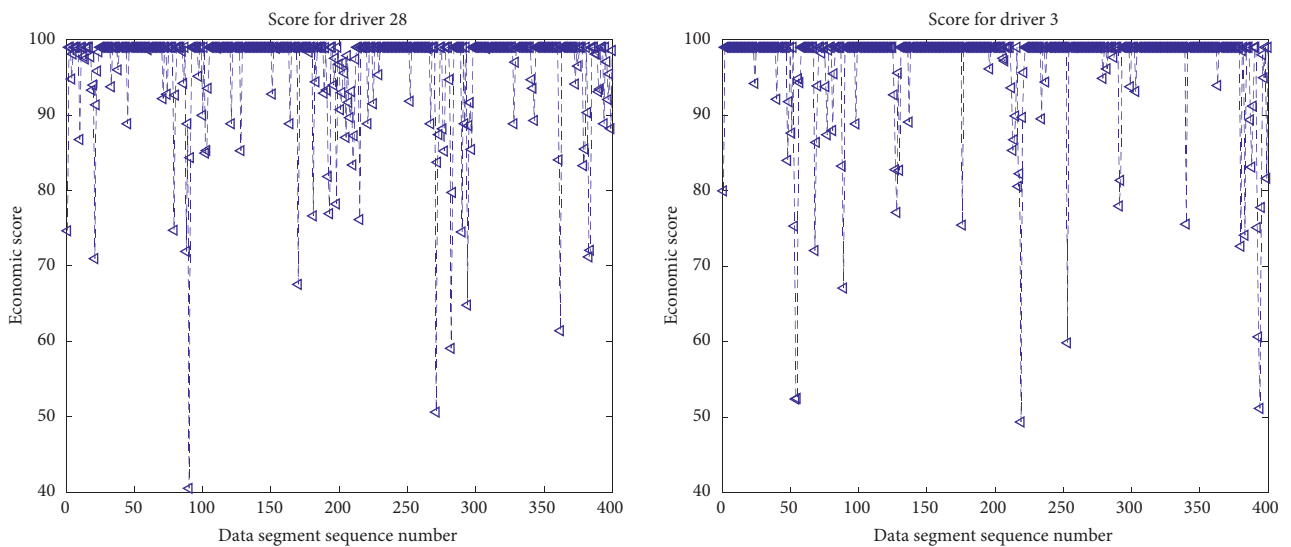


FIGURE 6: Part of the driver's score.

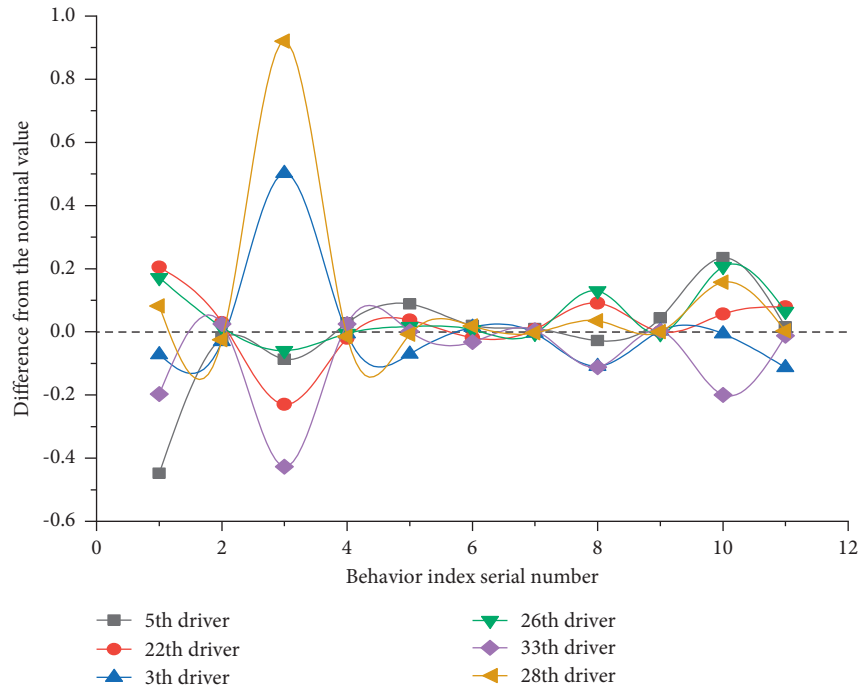


FIGURE 7: Test the low score index data.

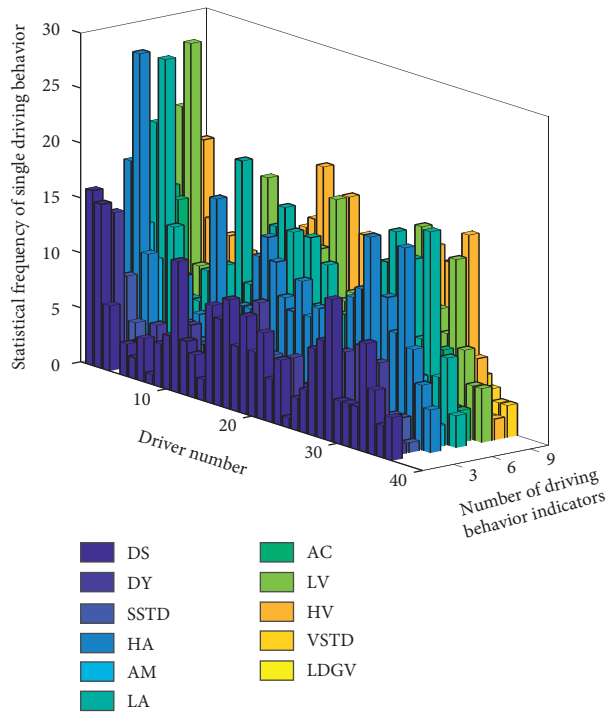


FIGURE 8: The statistical frequency chart of drivers' single driving behavior performance.

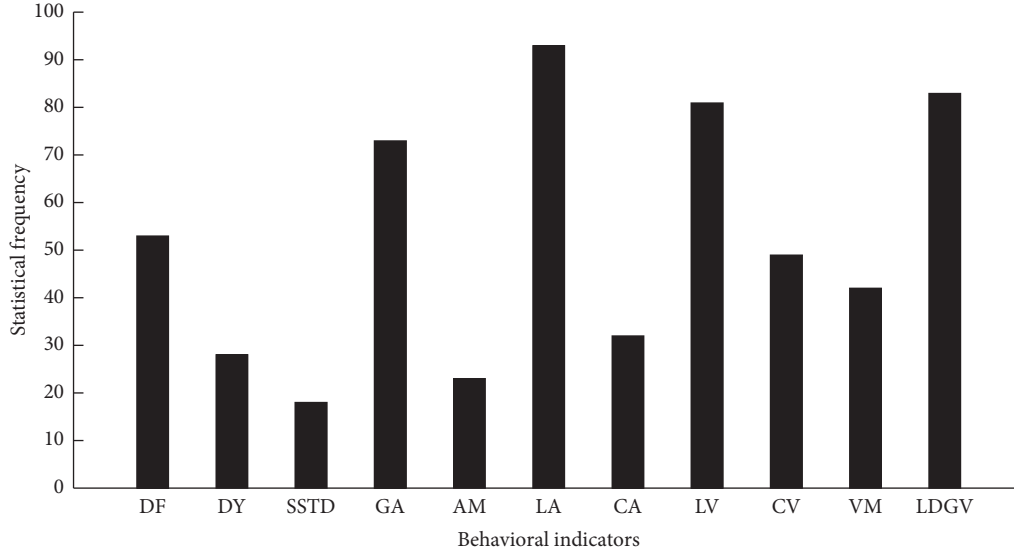


FIGURE 9: Overall frequency of driving behavior indicators.

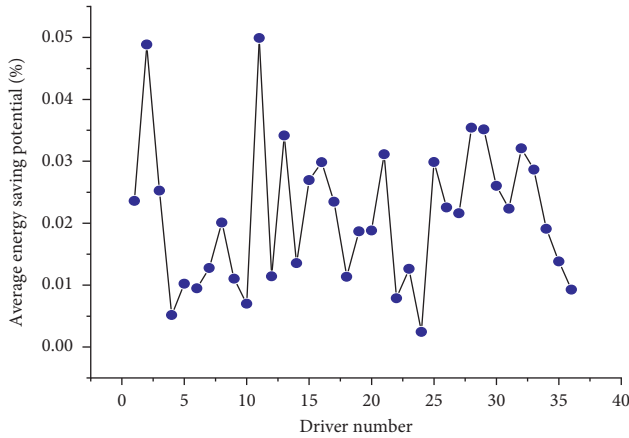


FIGURE 10: Average energy saving potential of drivers.

fuel consumption is given, which is further extended to all driving behavior economic indicators, as shown in equations (21) and (22).

$$F_{\text{loss}} = \sum_{i=1}^m \Delta F_i, \quad (21)$$

$$Q_{\text{loss}} = \sum_{i=1}^m \Delta Q_i. \quad (22)$$

It can be considered that there is a corresponding relationship between driving behavior loss score and driving behavior loss fuel consumption, that is, the improvement of each driving behavior score represents the reduction of fuel consumption and the improvement of fuel economy. Therefore, based on the highest score of driving behavior economy, a calculation method of energy saving potential is given based on the relationship between driving behavior economy score and fuel consumption.

$$\beta = \frac{F_{\text{loss}}}{F_{\text{max}}} \times 100\%. \quad (23)$$

By analyzing and calculating the energy saving potential of different drivers, the results are shown in Figure 10 in which drivers 2 and 11 have higher average energy saving potential compared with other drivers, which has a large space for optimization. The average maximum energy saving potential is 4.98%.

5. Conclusions

In this study, based on correlation analysis and fuzzy comprehensive hierarchical evaluation algorithm, a driving behavior economy evaluation system is established and a calculation method of energy saving potential is proposed. Correlation analysis plays a good role in screening driving behavior indicators. The fuzzy analytic hierarchy process (FAHP) has a strong applicability to the evaluation of driving behavior economy, which is influenced by multiple factors. The evaluation system and the calculation method of energy saving potential are tested by using the data of vehicle Internet of real cars. The results demonstrate the correctness of the work. In addition, the results of further analysis show that the overall driving behavior preference of drivers shows that the frequency of rapid acceleration and deceleration, low speed and low speed behavior is more frequent. The driving behavior preference performance of individual drivers is obviously different; The bad driving behavior of some drivers has a high energy saving potential of up to 4.98%. The study analyzes the differences in bad behaviors in the driver's economic evaluation, which can provide a theoretical basis for the targeted improvement of bad driving behaviors of drivers, and at the same time, the energy conservation analysis provides a basis for the formulation of the subsequent optimization strategies for energy-saving driving behaviors. The research is mainly aimed at freight vehicles, and the relevant system parameters have some

limitations. The follow-up work should further explore the universality of different vehicle types and operating conditions.

Under the background of engineering education, the joint training mode combining theoretical research and engineering practice is more suitable for students to carry out graduation project research and cultivate applied talents for enterprises than the traditional single school training mode, which should be implemented in more university training plans.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Acknowledgments

This work was supported in part by the Science and Technology Major Project of Guangxi under Grant AA18242033, Project of Guangxi key Research and Development under Grant AB21196029, Guangxi Natural Science Foundation Program Grant 2020GXNSFAA159081 and 2018GXNSFAA281276, Scientific Research and Technology Development in Liuzhou under Grant 2020GAAA0404, 2021AAA0112 and 2021AAA0104, Guangxi Science and Technology Base and Special Talents Program Grant 2018AD19077, Guangxi Key Laboratory of Manufacture System and Advanced Manufacture Technology under Grant 17-259-05-009Z, Guangxi Higher Education Undergraduate Teaching Reform Project under Grant 2021JGA180, 2020JGA173, and JGY20211085, and Teaching Reform Project of Guilin University of Electronic Technology under Grant JGB202002.

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