Dynamic game pricing model of car-free carrier platform based on GA-BP theory

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Abstract. With the rapid development of China's logistics industry, transport demand continues to be strong, and how to scientifically give platform pricing to achieve rapid transactions and reduce operating costs is a major problem. Firstly, in order to solve this problem, after collecting data from the car-free carrier company P, due to the excessive influence factors of the data, it is necessary to clean the data and normalize the data. Six indexes that affect the pricing are screened out by the grey correlation model, which are total mileage, total line cost, vehicle length, vehicle tonnage, transportation grade and the time needed for plan execution. In order to verify the rationality, we do multiple linear regression to the data. Secondly, in order to solve the nonlinear fitting problem, the improved initial value GA-BP model is introduced to perform data fitting and prediction, it is concluded that the first pricing is to achieve the required accuracy at n=94, and the error is less than 0.1% when the number of iterations no more than 100, which verifies the model is suitable for such problems. Lastly, In order to simulate the dynamic pricing process of the platform, it is required to predict three times of pricing. Based on the first pricing and known data, a neural network decision tree prediction model based on game theory is established. The dichotomy is applied to the value of information entropy to measure the proportion of price adjustment, and a conclusion is drawn. When the information entropy value I>26.7204, the second price adjustment decreases by 3.87% ,and the third price adjustment decreases by 0.39% . When the information entropy value I>26.7204, the second price adjustment decreases by 1.64% ,and the third price adjustment decreases by 1.27%.

1. Introduction
Since the reform and opening up, the "China Speed" has shocked the world, which is inseparable from the improvement of infrastructure construction. Under the superior highway construction, road transportation has naturally become the main force of transportation. However, due to the impact of weakening overseas demand, rising labor costs and inflation, China's transportation market is relatively tight, and the status of transportation companies is "more, small, scattered, weak" (Dong Na,2017)[2], transportation costs are always in a high position, small Logistics companies and individual transportation companies account for 90% of the market. The distribution of cargo and vehicle sources is relatively uneven in space, and the release of cargo source information is relatively closed. In this context, the operating model of car-free carriers came into being.

At present, many existing domestic car-free carrier platforms mainly provide car and cargo information, do not carry out actual road cargo transportation, and the service scope is relatively small.
The platform-based car-free carrier cannot guarantee integrity certification and cargo safety guarantee. Issues such as these provide legal protection. Many individual vehicle owners and small third-party freight companies are engaged in freight business, but there are problems with chaotic operations, such as blurred responsibilities, weak solvency, and low service levels. The end result is lower efficiency of matching goods and vehicles, and higher logistics input costs.

For the study of this problem, most of the domestic and foreign countries tend to qualitatively make fuzzy statistics on the results that have occurred in the market. Most of them are judged only by experience, and a few use data to study, but most of them optimize the freight route to a certain extent. Therefore, it is of great practical significance to study a complete pricing system to optimize the transportation capacity organization model and regulate transportation in the chaotic market.

2. Literature review

2.1. Industry overview
In the era of "Internet +", the freight mode of "Internet + truck" directly contributed to the birth of "car-free transportation". With its excellent resource integration ability, flexible price, huge user market and other advantages, the car-free transport platform began to gradually replace the traditional logistics and become the main force of freight logistics.

2.2. Current status of freight rate research
It is divided into two directions, one is the research on the macro policy, market analysis and existing problems of freight rates, and the other is the research on freight pricing.

2.2.1. Market Analysis. In foreign countries,(Spulber,1982)[11] analyzes the influence of market volatility on the two from the game relationship between the platform and consumers;(Kenneth,1997)[13] studies whether freight regulation is required by the government and whether there is excess capacity; Based on empirical evidence, (Thomas,1989)[12] investigates whether government regulation affects the scale of the platform.

In China, (Dong Na,2011)[2] proposed the need to scientifically control the car-free carrier platform and made a few comments on the market; (Wang Yafei, Yang Lei,2008)[17] proposed the need for express delivery targets for the characteristics of China’s express cargo and transportation needs Market segmentation positioning and suggestions for improving freight product design.

2.2.2. Freight Rate. In foreign countries, (Ferdinand, 2013) [16] uses a nonlinear integer programming model to calculate the expected profit maximization to solve the problem and solve the model based on genetic algorithm;(Adler, 2008)[14] introduces a game model between traffic modes to influence the factors affecting pricing.

In China,(Fang qi wen,2017)[1] proposed to use multiple linear regression and improved BP neural network processing; proposed to list the factors that have an impact on freight rates, and made recommendations; (Nie Fuhai, Li Diansheng)[7] Propose a game theory model of the car-free transportation platform under asymmetric information.

2.3. Overview of innovations and models
In summary, there are many qualitative researches on market freight pricing issues at home and abroad, and there are few studies on price setting. Most of them are based on economic phenomena, and there are few quantitative studies on the impact factors of freight rates. The method is statistical method and traditional BP neural network. There is no GA-BP algorithm and neural tree prediction model based on game theory.

This article starts from the influencing factors. First, the data is cleaned, a reasonable quantitative analysis model of influencing factors is established, and the factors that have a significant impact on line pricing are selected, and the degree of influencing factors on pricing is quantified. Secondly, we
use the BP neural network training function to continuously Trial and error, reverse feedback to obtain a training function with a high degree of fit for nonlinear problems, but in order to prevent the initial threshold of the traditional BP neural network from causing too many iterations, resulting in a limited iteration of the results can not be solved, introduced The genetic algorithm optimizes the initial threshold to form a BP neural network based on genetic algorithm to increase its accuracy and operation speed. It is called the GA-BP model, which can calculate the initial value of the platform pricing. Finally, in order to quantitatively and dynamically analyze the reduction bargaining process, a neural tree model is introduced to simulate and predict the value, which is called a neural network decision tree prediction model based on game theory. By obtaining the information entropy, the first time and the second time are obtained. The conclusion of price adjustment.

3. Research hypothesis

3.1. External macroeconomic factors

Due to the impact of external factors such as economic development level and fuel price on truck transportation costs and transportation prices, due to the relatively constant economic development level, GDP can be regarded as its indicator(Fang Qiwen, 2017)[1]To ensure the stability of the model, the following assumptions are made here:

H1: During data collection, GDP fluctuations are not included in the influencing factors
H2: Fuel prices are relatively constant during the data collection period

3.2. Market volatility

Extreme market conditions will affect the number of regression iterations of the model, which will affect the accuracy of the model.

H3: No market shrinkage or expansion in the short term

3.3. Uncontrollable factors

In the empirical stage, I will obtain the freight platform data of P Company, desensitize and use it for data analysis in this paper.

H4: Empirical data collected by P Company is true and valid

4. Theoretical Model

4.1. GA-BP neural network

StepI: Initialization
To measure the number of neural iterations(Si Shoukui, 2011)[3], set the maximum number of network trainings and the corresponding error conditions, and set the initial weights and thresholds based on this condition.

StepII: Positive feedback process
(a) Input training sample, set (X,p, T,p), p = 1, 2, ..., P
(b) For each sample value entered by (a), it is calculated in the following order

\[ g_j^p = f\left(\sum_{i=0}^{n} w_{ji} h_j^p\right), \]
\[ h_j^p = f\left(\sum_{j=0}^{n} w_{ji} h_j^p\right), \]
\[ y_j^p = f\left(\sum_{i=0}^{n} w_{ji} h_j^p\right) \]

StepIII: Error reverse feedback calculates the equivalent error of each layer of neurons, starting from the output layer, calculating to the input layer, and then returning to the reStep\^2, after obtaining the equivalent error, performing forward propagation calculation and error back propagation on other training sample pairs until all training sample pairs have been similarly calculated.

StepIV: Adjust the connection weight of each layer, press the following:
\[ w_{q}(n+1) = w_{q}(n) + \eta \sum_{p=1}^{s} \delta_{p}^{q} h_{i}^{p} \quad w_{j}(n+1) = w_{j}(n) + \eta \sum_{p=1}^{s} \delta_{p}^{j} h_{j}^{p} \quad w_{i}(n+1) = w_{i}(n) + \eta \sum_{p=1}^{s} \delta_{p}^{i} h_{i}^{p} \]

Modify the connection weights of each layer, \textit{Step 5} return to the \textit{Step 2}; then carry out the forward calculation according to the weights and thresholds just calculated, if the accuracy requirements are met, for each pair of training samples, its output layer neurons meet the precision requirements [15]:

\[ |t_{p} - y_{p}| < \varepsilon \quad p = 1, 2, \ldots, a \quad \varepsilon \]

for a given precision requirement, when the accuracy requirement is met, the network training is completed, otherwise the iteration continues until the requirement is met.

### 4.2. Neural network decision tree prediction model based on game theory

The specific steps of the improved C45 algorithm construction based on this question ID3 [7] are as follows:

\textit{Step I} : Data discretization

1. There are \( n \) sample data. According to the continuity of the function, the maximum and minimum values can be removed and set to \( G_{1}, G_{2} \).
2. Perform discrete interpolation and insert \( n \) data into \( [G_{1}, G_{2}] \) to form \( n+1 \) data.
3. Interpolation, and take the middle point, respectively, \( R_{i} = \frac{a_{i} + a_{i+1}}{2} (0 < i < n) \) as the segmented point, and divided into small intervals.

\textit{Step II} : Mark information entropy

The ratio of the gain value of each attribute to the information gain in Annex 2 is calculated, and the attribute with the highest information gain ratio is tested, marked, and the sample is divided.

\textit{Step III} : Iterative recursion

A value of a node may correspond to itself, recursively execute a subset of each possible value of the sample to the root node attribute, and recursively execute \textit{Step 2} on the subset of the sample until the decision tree is generated.

\textit{Step IV} : Get the predicted results.

### 5. Empirical Analysis

#### 5.1. Data collection

Company P is a "car-free carrier platform" company with a history of 5 years. We will collect data on the entire process from platform order to transaction from January to December 2019, and conduct desensitization processing. The treatment will be applied to the empirical model.

#### 5.2. Data screening and processing

##### 5.2.1. Data normalization

In order to facilitate data processing and eliminate dimensions [4], we used Z-score standardized method to normalize the data. The formula is:

\[ \alpha^{*} = \frac{a - \mu}{s} \]  \hspace{1cm} (2)

Among them, \( \mu \) represents the average value of all sample data, \( s \) is the standard deviation of all sample data, the data processed by this method conforms to the standard normal distribution, and the standardized index value obtained.

##### 5.2.2. Grey relational analysis degree

The calculation steps of the grey correlation analysis degree are:
It is necessary to determine the comparison object (the preliminary determination of the impact index factors) and the reference series (pricing) [7]. There are a total of 6 evaluation objects, and the reference number is listed as follows:

\[ X_i = (X_i(1), X_i(2), \ldots, X_i(n)), i = 1, 2, \ldots, m \]  

(3)

The comparison sequence is:

\[ X_i = (X_i(1), X_i(2), \ldots, X_i(n)), i = 1, 2, \ldots, m \]  

(4)

Normalize the research sequence:

\[ X_i^{r(k)} = \frac{X_i^{r(k)}}{X_i^{(1)}} \]  

(5)

Find the difference between the explanatory variable (pricing) and the sequence of influencing factors:

\[ \Delta_i(k) = |x_i^r(k) - x_i^r(k)|, \Delta_i = (\Delta_i(1), \Delta_i(2), \ldots, \Delta_i(n)), i = 1, 2, \ldots, m \]  

(6)

(4) Find \( K_{max} \) and \( K_{min} \)

\[ K_{max} = \max_i \max_k \Delta_i(k) \quad K_{min} = \min_i \min_k \Delta_i(k) \]  

(7)

(5) Calculate the correlation coefficient.

\[ r_i = \frac{1}{n} \sum_{k=1}^{n} \xi_i(k), \xi_i(k) = \frac{K_{min} + \rho K_{max}}{\Delta_i(k) + \rho K_{max}} \]  

(8)

\( \rho \) is the resolution coefficient, \( \rho \in [0,1] \). In order to distinguish the coefficient, the general value is 0.5, and finally the grey correlation coefficient of each column is obtained.

(6) Calculate the grey correlation degree:

\[ r_i = \frac{1}{n} \sum_{k=1}^{n} \xi_i(k) \]  

(9)

**Table 1. Relevance of various factors.**

| Index                  | Correlation degree |
|------------------------|--------------------|
| Total mileage          | 0.91               |
| Planned execution time | 0.91               |
| Vehicle length         | 0.87               |
| Vehicle tonnage        | 0.86               |
| Transport grade        | 0.77               |
| Total line cost        | 0.97               |
Figure 1. Radar chart of influencing factors for line guidance.

Through the above calculation, the main factors and the corresponding degrees of correlation are obtained. Through the setting of weights, the different proportions are assigned, and the multiple linear regression is performed. Table 2 is obtained:

\[ y_i = \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + \beta_6 x_6 + u_i \] (10)

Among them, \( y \) indicates pricing, and \( X_1, X_2, X_3, X_4, X_5, \) and \( X_6 \) represent total mileage, planned execution time, vehicle length, vehicle tonnage, transportation class, and total line cost. \( u_i \) is the random error term.

From the table below, the fitting degree of the regression equation is 98.6%, indicating that the pricing can be better explained by the total mileage, planned execution time, vehicle length, vehicle tonnage, transportation class, and total line cost.

According to Stata's estimation results:

\[ \hat{y}_i = -201.725 + 1.350 x_1 + 0.341 x_2 + 47.149 x_3 - 19.514 x_4 + 0.708 x_5 - 15.595 x_6 \]

Table 2. Stata regression results display.

| price   | Coef  | St.Err. | t-value | p-value | [95% Conf Interval] |
|---------|-------|---------|---------|---------|---------------------|
| road    | 1.350*** | 0.065 | 20.72   | 0.000   | 1.223 – 1.478       |
| time    | 0.341*** | 0.025 | 13.70   | 0.000   | 0.292 – 0.389       |
| length  | 47.149*** | 12.683 | 3.72    | 0.000   | 22.289 – 72.010     |
| weight  | -19.514*** | 5.468 | -3.57   | 0.000   | -30.232 – -8.796    |
| roadcost| 0.708***  | 0.014 | 49.81   | 0.000   | 0.680 – 0.736       |
| transportrank| -15.595*** | 11.067 | -1.41   | 0.000   | -37.289 – 6.098     |
| Constant| -201.725** | 51.870 | -3.89   | 0.000   | -303.396 – -100.054 |
| R-squared| 0.986   | Number of obs | 16008.000 | Prob > F | 0.000              |

(*** p<0.01, ** p<0.05, * p<0.1)

5.3. Demonstration of Freight rate Model

5.3.1. GA-BP model. Based on the data after screening and normalization, the nonlinear data are fitted by GA-BP model, and the fitting degree is given, and then the first pricing is predicted, and through the anti-normalization of the first pricing, the following conclusions are obtained:

Figure 2. BP neural network flow chart.
The above results show that when the training function iterates to \( n = 94 \), the error of the training function is less than 0.1\%, indicating that the training function reaches the ideal convergence state within 100, indicating that the training is successful and can be used to predict the test group.

**5.3.2. Neural network decision tree prediction model based on game theory.** Based on the data after screening and normalization and the first pricing data, the C45 algorithm improved by the neural tree prediction model is used to set the weights using game theory to obtain different information entropy. According to the value of the information entropy, the different data gives the price adjustment ratio.

Finally, Take 100 sets of data for prediction, and compare with the actual situation, thus proving that the model has good practical value.
When the information entropy value $I > 26.7204$, lower the price by 3.87% for the second price adjustment and 0.39% for the third price adjustment.

When the information entropy value $I < 26.7204$, lower the price by 1.64% for the second price adjustment and 1.27% for the third price adjustment.

100 groups of data are used to predict and compare with the original data, the variance is less than 5%, which verifies the rationality of the model.

6. Discussion

6.1. Model advantages and disadvantages evaluation

6.1.1. Advantages. Establish a BP neural network model based on genetic algorithm. By choosing a good initial threshold, the problem of poor convergence of the BP neural network is solved, the number of iterations of the neural network is greatly reduced, and a higher accuracy can be obtained. Linear fitting model. You can train the value with high accuracy.

Use game theory to simulate the dynamic bargaining model of the platform and the driver, taking into account the interaction between the various factors, so as to derive the coping strategies for different parties.

Use the decision tree prediction model, adopt the improved C45 algorithm of ID3 algorithm, and get three times of pricing. Through the method of two classifications, quantify the simulated bargaining process.

6.1.2. Disadvantages. A BP neural network model based on genetic algorithm is established. By selecting a good initial value threshold, the problem of poor convergence of BP neural network is solved, the number of iterations of neural network is greatly reduced, and a nonlinear fitting model with higher accuracy can be obtained. The value with high accuracy can be trained.

Using game theory to simulate the dynamic bargaining model of the platform and the driver, the interaction between various factors can be taken into consideration, so as to obtain the coping strategies for different parties.

Using the decision tree prediction model and the improved C45 algorithm of ID3 algorithm, three times pricing is obtained. Through the method of two classification, the simulated bargaining process is studied quantitatively.

6.2. Prospect and extended application of the model
In addition to the car pricing platform, the problem of line pricing also exists in other areas such as air transportation, sea transportation, and rail transportation. Therefore, it can be applied in various transportation industries to reduce costs and improve enterprise efficiency. The BP neural network model we use not only can predict our pricing well, but also plays an important role in the field of artificial intelligence. Machine deep learning algorithms will also enter our lives [9].

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