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Extraction and Prediction System of Core Influencing Factors of Civil Aviation Transportation Benefit

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Abstract: Obtaining the influencing factors of transportation benefits and accurately predicting transportation benefits are the key premise for civil aviation transportation companies to formulate operation strategies. This paper makes research on the extraction and prediction system design of the core influencing factors of civil aviation transportation benefits. Because the system does not need the assistance of hardware equipment, the design is carried out on the determination of the collected data input and output, the data screening of the core influencing factors of the transportation benefits, the prediction results and error test, etc from the perspective of software, so as to achieve the accuracy of the extraction and prediction of the core influencing factors. The experimental results show that this system can effectively reduce the error of prediction results compared with the traditional system, and provide strong data support for civil aviation transportation.

Keywords: civil aviation transportation; benefit; core influencing factors; extraction; prediction

1. Introduction

The benefit of civil aviation transportation refers to the expected sales revenue of civil aviation transportation companies in the process of commercial operation on a specific route. This benefit index can be used to effectively measure the transportation management level of civil aviation. Whether the civil aviation transportation company can accurately control the key influencing factors of route transportation benefits and predict the future income level of specific routes is the basis for each civil aviation transportation company to formulate the correct route operation management strategy and improve the economic benefits of the route [1]. In addition, the launch strategy, revenue management scheme and flight planning of each route are realized based on accurate prediction of transportation benefits. At present, the commonly used method to extract the influencing factors of transportation benefits of civil aviation transportation companies is to take the macroeconomic indicators as the main influencing factors, and rarely analyze and extract the influencing factors from the micro perspective such as the capacity supply of specific routes. However, in the actual operation process of civil aviation transportation companies, it is often affected by the supply level of route operation [2]. Therefore, when extracting and forecasting the influencing factors of transportation benefits, we should not only consider the macro factors, such as the level of social and economic development, population density, residents' consumption capacity, but also consider the micro level factors, such as transport type, flight schedule arrangement, flight frequency and other factors. Therefore, through the above discussion, it is of great significance to accurately extract the influencing factors of civil aviation transportation and establish a method that can accurately predict the benefit of air route transportation for improving the competitiveness of civil aviation transportation companies in the market. Based on this, this paper carries out the research on the design of the extraction and prediction system of the core influencing factors of civil aviation transportation benefits.

2. Software Design of Extraction and Prediction System for Core Influencing Factors of Civil Aviation Transportation Benefits

The factors that influence civil aviation transportation efficiency mainly include the following aspects: passenger volume, direct impact, flight time, aircraft type, flight frequency, available seats, etc. The related real-time data information of the above factors can be directly obtained by the aviation control management center, so there is no need to use sensors, chips and other hardware equipment. Therefore, in this paper, when designing the core influencing factors extraction and prediction system of civil aviation transportation benefits, only the software part is designed in detail without considering the hardware content.

2.1. Input and output determination of collected data

In the system of this paper, the input and output of the collected data mainly rely on the internal data file management module. The data file management is mainly responsible for the management and update of various data in the basic database, thus to realize the operation of data editing, sorting, type definition and outlier detection [4]. The main management data include passenger volume, flight time, relevant time cycle, flight frequency, ticket price level, seat rate, etc. Therefore, in order to ensure the accurate the input and the output of the collected data and improve the performance of the system, quantitative analysis and principal component analysis can be carried out for several groups of collected data.

Firstly, the correlation coefficient of two groups of data series is calculated, and then the correlation degree between different data series is calculated. Two groups of different data series are set. The reference data sequence is P0, P0={p0(x), x=1, 2, …, n}; the comparative data sequence is Pi, Pi={pi(x), X=1, 2, ..., n ; i=1, 2, ..., m}. The correlation coefficient of the two groups of data series is calculated as follows:

$$d_{0i}(x)=\frac{\min_i \min_x |a_0(x)-a_i(x)| + d \max_i \max_x |a_0(x)-a_i(x)|}{|a_0(x)-a_i(x)|} \quad (1)$$

In formula(1), $d_{0i}(x)$ represents the correlation coefficient of two groups of data series; $a_0(x)$ is the dimensionless reference data series; $a_0(x)$ is the dimensionless comparison data series; d is expressed as the resolution coefficient, and the value of d is [0,1]. According to the actual situation of civil aviation transportation, the value of d is usually 0.4. The introduction of resolution coefficient d can objectively eliminate the data of acquisition points with large deviation and avoid the distortion of correlation degree in the subsequent prediction of transportation benefits. Formula (2) is the calculation formula of correlation degree between different data series

$$l_{0i}=\frac{1}{m}\sum_{x=1}^{m} d_{0i}(x) \quad (2)$$

In formula (2), l_{0i} is the correlation degree between different data sequences. In order to ensure the objectivity of the system in this paper in the extraction process of core influencing factors of civil aviation transportation benefits, this paper sets that when $0 < l_{0i} \leq 0.25$, the correlation between two groups of different data series is weak correlation; when $0.25 < l_{0i} \leq 0.75$, the correlation degree between two groups of different data series is strong correlation [5].

Secondly, the principal component analysis is carried out on the collected data and many linear correlated influencing factors are converted into a few linear uncorrelated influencing factors, thus cutting off the interference of correlation in the process of system analysis and convert high-dimensional problems into low-dimensional problems. This can provide data basis for the subsequent screening of core influencing factors that affect the benefits of civil aviation transportation.

2.2. Data screening of core influencing factors of transportation benefits

Because the units and levels of magnitude of different influencing factors are not comparable, the system cannot directly screen the data of core influencing factors of transportation efficiency, so the data input into the system needs to be dimensionless to eliminate the influence of dimension on the collected data. This paper adopts the method of standardizing the input data to make the standardized data fall into the range of [- 1, 1]

$$k_i = 2\times\frac{(l_i - l_{\min})}{(l_{\max} - l_{\min})} - 1 \quad (3)$$

In formula (3), k_i is the input data after standardization; l_i is the original input data sequence; $l_{\min}$ is the minimum value of the original input data sequence; $l_{\max}$ is the maximum value of the original input data sequence. Input the standardized data into the system; calculate it according to the formula (2) above, judge the correlation degree of the obtained l_{0i} value according to the above standard. If the correlation is weak, it means that the influencing factors of the data are not the core influencing factors, so they can be filtered; if the obtained l_{0i} value is strong correlated, it indicates that the influencing factors of the data are the core influencing factors, which can be screened out.

2.3. Prediction results and error test

In this system, the RBF neural network prediction model is used to predict the civil aviation transportation benefits. After inputting the selected data series into the model, the model will automatically determine the center and linear layer weights of the radial basis function. The shape of the radial basis function Gaussian function and the threshold speed value in the model need to be controlled by the system [6]. The larger the speed value obtained by the model, the fatter the curve is; the smaller the speed value, the thinner the curve is. Therefore, according to this characteristic, the speed value can be used as the distribution density value of radial basis function. When the speed value is larger, the neurons participate in the response in the same distance will be more and the prediction performance results will be smoother, which can predict results more accurately.

In order to further ensure the reliability of the prediction results made by the system of this paper, we need to check the error after obtaining prediction results. In this paper, the absolute average percentage error-checking algorithm is used

$$MAPE=\frac{1}{c}\sum_{i=1}^{c}\left|\frac{Y(x)-\hat{Y}(x)}{Y(x)}\right| \quad (4)$$

In formula (4), $MAPE$ is the prediction error; C is the prediction times; $Y(x)$ is the actual transportation benefit of civil aviation transportation; $\hat{Y}(x)$ is the actual transportation benefit of civil aviation transportation in the system of this paper. A large number of training samples are used to train the model. When the obtained $MAPE$ value exceeds 0.02, it means that there is a certain error between the prediction result and the actual situation, and the training operation needs to be repeated again until the final $MAPE$ value is less than 0.02, which means that the prediction result of the system is accurate at this time.

3. Simulation Experiment

3.1. Experimental preparation

This paper selects a certain route in a civil aviation transportation company as the experimental object. Inputs the operation parameters of the route in the past two years into the simulation experimental software, construct the simulation experimental platform, and use the system of this paper and the traditional system to carry on the empirical prediction of the transportation benefit of the route in the next two years. Table 1 shows the historical parameter information input in the two groups of systems.

Table 1. Historical parameter information input in two groups of systems

Operating quarter	Passenger load factor	Ticket price	Number of passengers	Flight number
The first quarter of the first year	81.24%	960 Yuan	126	4 times / day
The second quarter of the first year	91.24%	1018 Yuan	105	3 times / day
The third quarter of the first year	93.48%	1020 Yuan	112	3 times / day
The fourth quarter of the first year	90.18%	1028 Yuan	95	5 times / day
The first quarter of the second year	86.14%	960 Yuan	103	3 times / day
The second quarter of the second year	91.54%	980 Yuan	128	3 times / day
The third quarter of the second year	93.48%	1010 Yuan	94	4 times / day
The fourth quarter of the second year	86.15%	1035 Yuan	98	5 times / day

Input all the above historical data into the system of this paper and the traditional system respectively to predict the transportation benefit of the route in the next year. The prediction results are compared with the real values, and the corresponding errors are obtained by using the above formula (4).

Using the trained system and the traditional system respectively, complete the comparative experiment according to the above preparation, and then according to the experimental results, get the comparison table of experimental results as shown in Table 2.

3.2. Experimental results and analysis

Table 2. Comparison of simulation results

Operating quarter	The system of this paper			Traditional system		
	Predicted value	Actual value	Error value	Predicted value	Actual value	Error value
The first quarter	35.8465 million Yuan	35.764 million Yuan	<0.02	35.3548 million Yuan	35.764 million Yuan	<0.02
The second quarter	32.5754 million Yuan	32.4547 million Yuan	<0.02	31.2384 million Yuan	32.4547 million Yuan	>0.02
The third quarter	25.3745 million Yuan	25.341 million Yuan	<0.02	25.6517 million Yuan	25.341 million Yuan	<0.02
The fourth quarter	26.3454 million Yuan	26.4184 million Yuan	<0.02	24.544 million Yuan	26.4184 million Yuan	>0.02

In Table 2, through the error data, we can see that all the error value of the system in this paper is less than 0.02, while the error value in the traditional system is more than 0.02 when it predicts the second quarter and fourth quarter of the next year. If the error value is lower than 0.02, it means that the prediction result is in line with the actual situation, and if the error value is more than 0.02, it means that the prediction result is not consistent with the actual situation. Therefore, the simulation experiment proved that extraction and prediction system of the core influencing factors proposed in this paper can get more accurate prediction results, effectively find out the core influencing factors affecting the transportation benefits, and accurately predict the future transportation benefits according to the core influencing factors.

4. Conclusion

For the civil aviation transportation company, the transportation benefit is its foundation. The application of the extraction and prediction system of the core influencing factors of the civil aviation transportation benefit proposed in this paper can make the civil aviation transportation company more scientifically obtain the key factors of the transportation benefit and the economic benefits that can be harvested in the future. However, due to the limited ability, it is found that there is a big error in the prediction of transport benefits over 5 years. Therefore, in the follow-up study, more in-depth research should be carried out to ensure the sustainable development of civil aviation transportation.

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