Evaluation of freight logistics delayed efficiency in China

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Abstract: In order to improve the development quality of China's freight logistics, improve the efficiency of resource utilization, the article uses ARIMA-SVR-DEA method to forecast the freight logistics in our country delayed data and calculate the delayed freight logistics efficiency, and the results show that the unreasonable utilization of resources is the reason for the inefficiency of freight logistics, which provides a reference for the development of freight logistics industry.

1. Introduction

Freight logistics is an important part of China's logistics industry. It is of great significance to evaluate the efficiency of freight logistics for the innovative and efficient development of China's logistics industry[1]. Based on the research of Shabanpour[2] and Zhang[3], the ARIMA-SVR-DEA method was established. Firstly, ARIMA-SVR was used to predict the delayed input-output data, and then DEA was used to calculate the delayed efficiency value. Through the effective combination of ARIMA, SVR and DEA to guide the efficient and energy conservation development of freight logistics in China.

2. Establishment of freight logistics delayed efficiency evaluation model

1) Obtain China's freight logistics input-output data;
   2) Time sequence diagram method and ADF test method are used to test the stationarity of input-output data, and the d-order difference is used to stabilize the unstable sequence;
   3) The order of input-output time series is determined by observing the autocorrelation graph and partial correlation graph of input-output;
   4) Observe the autocorrelation graph and partial correlation graph of residuals of input-output and uses Ljung-Box test to check whether the residuals are white noise sequences;
   5) Take the input-output residual sequence as the input data of SVR and use the cross-validation method to determine the optimal c as the penalty factor and σ as the tolerance factor;
   6) Establish ARIMA-SVR model to predict delayed input-output data and their variation trend;
   7) Analyze the prediction results and actual errors of ARIMA-SVR, and evaluate the prediction accuracy;
8) Combining the predicted input-output delayed data with the known input-output data, the DEA model was used to calculate the delayed efficiency of freight logistics.

3. Evaluation of delayed efficiency of Freight logistics in China

Freight logistics activities in China from 1999 to 2018 were selected as the decision unit, and the input data of the decision unit were the number of people employed ($x_1$), the number of vehicles owned by highway operators ($x_2$) and the average length of cargo transportation ($x_3$), the output data is the volume of goods transported ($y$). The quantitative data are all from the official website of the National Bureau of Statistics.

3.1. ARIMA input and output forecasts

1) Stationarity test. Taking $y$ as an example, observe the time sequence diagram of $y$. It can be intuitively seen from Figure 1 that the curve presents a continuously rising trend in a long time. Then, the ADF unit root test was used to obtain $P=0.3174>0.05$. The null hypothesis was not rejected and the time series was considered unstable.

The time series is considered to be stable after observation of Figure 2. Then, the ADF unit root test $P=0.0355<0.05$ is performed to reject the null hypothesis and the time series is stable after the second difference.

2) Model order determination. After second-order difference, the sequence tends to be stable, and autocorrelation and partial correlation are shown in Figure 3: the autocorrelation function values of the second-order difference sequence all fall within the range of two standard deviations after the third-order difference, while the partial correlation function values all fall within the range of two standard deviations after the difference, so choose to build ARIMA(0,2,3) model[4].

FIG. 1 Sequence diagram of $y$

FIG. 2 Sequence diagram of second-order differential $y$
3) Residual test. By observing residual autocorrelation and partial correlation (Figure 4) and $p=0.7642>0.05$, it can be considered that the second-order difference time series is a stationary white noise series. Therefore, it can be considered that the fitting effect of this model is relatively good and can be used for prediction.

Similarly, according to the stationarity test, model order determination and residual test, the ARIMA model of $x_1$, $x_2$, and $x_3$ can also be obtained, as shown in Table 1.

3.2. The SVR modifies the ARIMA model
The nonlinear residual sequence obtained by subtracting the actual value of capital input and the fitting value of $y$ is input into SVR for training because the data quantity is less, 5 sets of data cycles were made for residuals, that is, 14 residuals were sequentially arranged each time, the first 4 sets of arranged data were used as the input of the SVR model, and the fifth set of data was used as the output of the SVR model; The model was trained by using the LIBSVM toolbox, and the penalty factor $c=6.9644$ and the tolerance factor $\sigma=6.9644$ in SVR were selected by using the 10-fold cross-validation method (Figure 5).

Similarly, the optimal parameters $c$ and $\sigma$ of $x_1$, $x_2$, and $x_3$ can be obtained by cross-validation. The results are shown in Table 1.
3.3. **ARIMA-SVR combination model test**

In order to evaluate the error between the predicted value and the actual value, two indexes, MRE and fitting degree graph, were used to test the fitting effect of the model and the accuracy of the prediction. It can be seen from Table 1 that the MRE of the ARIMA-SVR model is improved to different degrees compared with the single ARIMA model. From the $y$-fitting figure (Figure 6), it is obvious that the ARIMA-SVR model has a stronger predictive ability.

| Indicators | (p,d,q) | MRE  | c   | σ   | MRE |
|------------|---------|------|-----|-----|-----|
| $x_1$     | (1,2,2) | 0.046| 24.251| 1.515 | 0.025 |
| $x_2$     | (5,1,5) | 0.079| 111.43| 0.870 | 0.058 |
| $x_3$     | (5,1,0) | 0.024| 36.758| 6.964 | 0.015 |
| $y$       | (0,2,3) | 0.029| 6.964 | 6.964 | 0.021 |

FIG. 6 Comparison of the fitting degree of model of $y$

3.4. **Delayed freight logistics efficiency evaluation**

The ARIMA-SVR model is used to predict the input-output delayed data of China's freight logistics in 2019-2021, and table 2 is obtained. DEAP software was used to calculate the freight logistics efficiency of China in 1999-2018 and 2019-2021 respectively, from 1999 to 2018, the average efficiency was 0.704. The freight efficiency was low and fluctuated (Figure 7), this is because the development of market
economy, the increase of government support and the increase of factor input have led to the rapid development of freight logistics and the gradual improvement of freight efficiency, however, the scale of freight logistics market is relatively low, which leads to the waste of resources and the reduction of efficiency. From 2019 to 2021, the delayed efficiency is 1.000, 0.994, and 1.000 respectively (see Table 3). Although it is non-DEA effective in 2020, the overall efficiency level is high.

According to the efficiency measurement results from 1999 to 2021, there is a redundancy of resource investment in non-DEA effective years, the non-DEA efficiency of freight logistics delayed efficiency in China is caused by the inadequate utilization of resources. Therefore, China's freight logistics industry in the future development should pay attention to the rational use of resources, improve the efficiency of resource utilization, with the least resource input to create the greatest use of value[5].

Table 2 Prediction of the variation trend of DEA indicators

| Decision-making unit | 2019     | 2020     | 2021     |
|----------------------|----------|----------|----------|
| x₁                   | 633.22   | 648.24   | 661.13   |
| x₂                   | 1412.72  | 1569.66  | 1687.34  |
| x₃                   | 393.13   | 397.74   | 397.42   |
| y                    | 546.49   | 565.94   | 587.35   |

FIG.7 Freight logistics efficiency values from 1999 to 2018

Table 3 The value of relaxation variable and efficiency of the decision-making unit

| Decision-making unit | 2019     | 2020     | 2021     |
|----------------------|----------|----------|----------|
| S₁                   | 0.000    | 3.715    | 0.000    |
| S₂                   | 0.000    | 8.995    | 0.000    |
| S₃                   | 0.000    | 5.126    | 0.000    |
| S₁⁺                  | 0.000    | 0.000    | 0.000    |
| S₂⁺                  | 0.000    | 0.000    | 0.000    |
| Efficiency           | 1.000    | 0.994    | 1.000    |

4. Conclusion
This paper evaluates the delayed efficiency of China's freight logistics by establishing the ARIMA-SVR-DEA combination model, the results show that the delayed efficiency of China's freight logistics from 2019 to 2021 is 1.000, 0.994 and 1.000, respectively, if the corresponding resources are invested according to the predicted input value, the utilization of resources is sufficient and the freight logistics efficiency will reach a higher level. By observing the non-DEA effective year, it can be known that the insufficient utilization of resources is the reason why freight logistics activities are not DEA effective,
therefore, China's freight logistics industry should pay attention to the reasonable allocation and use of resources in the future, to avoid excessive resource input leading to the low efficiency of freight logistics or too little resource input leading to insufficient output, so as to provide an important reference for the high quality and efficient development of China's freight logistics industry.

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