J Inf Process Syst, Vol.15, No.2, pp.305~319, April 2019
https://doi.org/10.3745/JIPS.04.0107

ISSN 1976-913X (Print)
ISSN 2092-805X (Electronic)

JOURNAL OF INFORMATION PROCESSING SYSTEMS JIPS

A Prediction Model of the Sum of Container Based on Combined BP Neural Network and SVM

Min-jie Ding*, Shao-zhong Zhang*, Hai-dong Zhong**,***, Yao-hui Wu*, and Liang-bin Zhang*

Abstract

The prediction of the sum of container is very important in the field of container transport. Many influencing factors can affect the prediction results. These factors are usually composed of many variables, whose composition is often very complex. In this paper, we use gray relational analysis to set up a proper forecast index system for the prediction of the sum of containers in foreign trade. To address the issue of the low accuracy of the traditional prediction models and the problem of the difficulty of fully considering all the factors and other issues, this paper puts forward a prediction model which is combined with a back-propagation (BP) neural networks and the support vector machine (SVM). First, it gives the prediction with the data normalized by the BP neural network and generates a preliminary forecast data. Second, it employs SVM for the residual correction calculation for the results based on the preliminary data. The results of practical examples show that the overall relative error of the combined prediction model is no more than 1.5%, which is less than the relative error of the single prediction models. It is hoped that the research can provide a useful reference for the prediction of the sum of container and related studies.

Keywords

BP Neural Network, Grey Relational Analysis, Sum of Container Prediction, Support Vector Machine

1. Introduction

Predicting the volume of container traffic is the basic premise for the container transportation area, the container system and container port planning and layout. Predicting the volume of container traffic also plays a very important role in determining the port's direction of development, its scale of infrastructure investment, berth locations, the business strategy, etc. At present, studies on the numbers of containers are mainly based on the factors influencing the container volume and the prediction model of container volume. The study of the influencing factors can be mainly divided into economic and non-economic factors [1]. Macroeconomic indicators are usually treated as economic factors, while the related indicators of the port's construction are generally treated as the non-economic factors. Nevertheless, these indexes are usually abstract, and they cannot directly reflect the characteristics of foreign trade containers and the reasons for changing trends. The use of unrepresentative indexes for prediction can reduce its precision, making the results unreliable. The volume of foreign trade containers is subject to many influencing

Manuscript received July 21, 2017; first revision September 8, 2017; accepted October 23, 2017.

Corresponding Author: Hai-dong Zhong (zhd_1981@163.com)
* School of Electronic and Computer Science, Zhejiang Wanli University, Ningbo, China (dlut_z88@163.com, dmj1475968772@163.com {253929699, 1710520132}@qq.com)
** School of Logistics and E-commerce, Zhejiang Wanli University, Ningbo, China (zhd_1981@163.com)
*** Key Laboratory of Geographic Information Science, Ministry of Education, East China Normal University, Shanghai, China (zhd_1981@163.com)

factors, and is notably affected by related import and export elements. For the importing country, it can be limited by its own national politics, economy, culture, and the distance of the exporter; the exports of the exporter will be influenced by the respective location, the political environment, the development level of the economy, and the reserves of resources and other factors [2]. The present study of prediction models mainly adopts time series analysis and causality prediction methods such as moving averages, exponential smoothing, trend extrapolation, regression analysis and so on [3-6]. However, the prediction precision of these approaches is somewhat limited.

The volume of foreign trade containers has many influencing factors, and it is difficult to select indexes from the great quantities of data because it is usually unknown whether one index is influenced by the forecasting object [7,8]. In the data mining field, there are many models that can be used to find the relationship between massive factors. Among these models, gray relational analysis is one of the most well-known approaches. It was initially applied to determine the suitable selection of machining parameters for the wire electrical discharge machining (Wire-EDM) process [9]. Later, many scholars used this method to select the influencing factors that are most closely related to the forecasting object. It has been proved that the gray relational analysis method can make the prediction index system more scientific and accurate [10]. The back-propagation (BP) neural network is one of the most widely applied neural network models that can be used to learn and store a great deal of mapping relations of an input-output model. It is now widely applied in many areas such as pattern recognition, classification, data compaction, data prediction, etc. [11,12]. However, the learning speed of the BP neural network is usually very slow because it requires small learning rates for stable learning. Support vector machine (SVM) is another popular algorithm for supervised machine learning and classification. It has many unique advantages in solving small sample, nonlinear and high dimensional pattern recognition problems [13]. In addition, a proper kernel function is one of the most important factors in applying SVM, and error of the input data needs to be well controlled. It can be found from the current studies that both the combined BP neural network and the SVM have their advantages and disadvantages [14,15]. Due to the complexity of the influencing factors in container volume prediction, joint forecasting models can take the advantages of each single one, and improve the accuracy significantly. In this paper, we propose a gray relational analysis approach to select indexes of container volume and combine the BP neural network and SVM [16] methods to forecast the foreign trade container volume.

The remainder of the article is organized as follows: backgrounds and container volume related indicators, technologies, and measures are reviewed in Section 2. Then detailed concepts of the proposed prediction models and algorithms are explained in Section 3. Experiments on publicly available ports-of-entry yearbook data and analysis of the results are conducted in Section 4. Finally, we conclude the paper in Section 5.

2. Related Works

At present, the topic of container volume prediction is being intensively investigated by scholars all over the world. Their studies mainly focus on two aspects. On the one hand, they aim to discuss the prediction indexes system, and how to select the main influencing factors from numerous other indicators. On the other hand, they select, analyze, establish and optimize the prediction models, and evaluate the predicted results accordingly.

2.1 Container Volume Impact Factors

Research related to foreign trade container volume impact factors is a hot topic. In the existing studies, the related indictors fall into three categories [17-19]: world economy environment, regional economy scale, and technological advances.

(1) The environment of the world economy factors: Foreign trade can be easily influenced by the environment of the world economy, and especially changes in the international exchange rate. For example, the exchange rate in bilateral trade plays a significant role in promoting or inhibiting imports, which affects exports. If the exchange rate changes, the volumes of imports and exports from importing and exporting countries will be impacted almost immediately. In the last 3 years, the growth rate of China's foreign trade container volumes has decreased year by year. One important reason is that, along with changes in the industrial structure and increased labor costs and raw materials prices, many developed countries' processing factories have turned to Southeast Asia with its cheaper labor.

(2) The regional economy scale factors: The scale of the regional economy affects the foreign trade container volumes directly. For the importing country, the scale of its regional economy influences its purchasing power and the relative price of imported goods. For the exporter, the scale of its regional economy influences export volumes directly. These influencing factors can be reflected in the GDP, the total imports and exports of goods. With the continuous improvement of foreign trade policies in China, the total imports and exports of goods increased from \$0.28 billion to \$4.30 billion between 1995 and 2014 (https://tradingeconomics.com/china/indicators). Along with more countries signing free trade agreements, the reduction of tariffs, and the popularity of cross-border e-commerce, the quantity of bulk cargo will increase significantly.

(3) The technological advance factors: With the help of progress in container operations and process related science and technology, diverse types of special containers are coming into being to meet the transportation requirement of ever-increasing special goods. Meanwhile, the utilization rate of containers is improving, and both the box change rate of common containers and dead weight of the average heavy box are increasing. However, the appearance of high-value products usually leads to fewer container needs.

2.2 Container Volume Prediction Methods

In general, there are two kind of container volumes prediction models, qualitative and quantitative [20,21].

(1) Qualitative prediction models: Qualitative prediction models are widely used to analyze the factors influencing container volumes. Also, they are popularly applied to predict the total number of containers. Chou C-C, et al. estimated the container imports of Taiwan by using an improved regression prediction model. They verified that the model had greater predictive accuracy [4]; Hwang, et al. [5] proposed a fuzzy-neural network model GMDH to predict the container volumes for the port of Busan in South Korea; Freitas and Rodrigues [14] studied the feasibility of combining neural network models with the Gaussian radial basis function network approach, and then put forward a linear joint estimation model that was expanded from many commonly used methods; Although, much attention has been paid to this research area, many scholars have proved that the accuracy of the qualitative prediction models is rather low and the results are inclined to be influenced by many subjective elements [22,23].

(2) Quantitative prediction models: Quantitative prediction models are usually based on the neural network, time series analysis method, historical data extrapolation, system dynamics, and so on. These kinds of models can predict effectively, but they also have insufficient fixed predictive indexes and are low in precision. Makridakis and Winkler [1] found that the accuracy of the combined prediction models is higher than the single models in research using time series: when two kinds of prediction models are combined, the error is reduced by 7.2%; when five kinds of prediction models are jointly used, the error can be reduced by 16.3%. Similarly, Huang et al. [24] proposed a partially combined prediction framework for container throughput based on big data composed of structured historical data and unstructured data, and predicted the container traffic through Qingdao Port using the combined prediction approach. Wu [25] presented a load forecasting model based on hybrid particle swarm optimization with Gaussian and adaptive mutation (HAGPSO) and a wavelet v-support vector machine (Wv-SVM).

At present, a great many studies focus on container volume prediction models, while less attention is paid to the factors that influence the prediction's object and the predicted result accuracy. Therefore, we propose a joint approach to predict the sum of containers. First, the paper analyzes the factors influencing foreign trade container volumes through gray relational analysis, which can simplify the complexity of the prediction, and reduce the problem of prediction accuracy caused by small amounts of data. Then, the paper puts forward a combined prediction model based on a BP neural network and SVM, and aims at solving the shortcomings of the fixed index and the lower predictive accuracy of the previous prediction models.

3. Prediction Model and Algorithm

3.1 The Combined Prediction Flow Chart

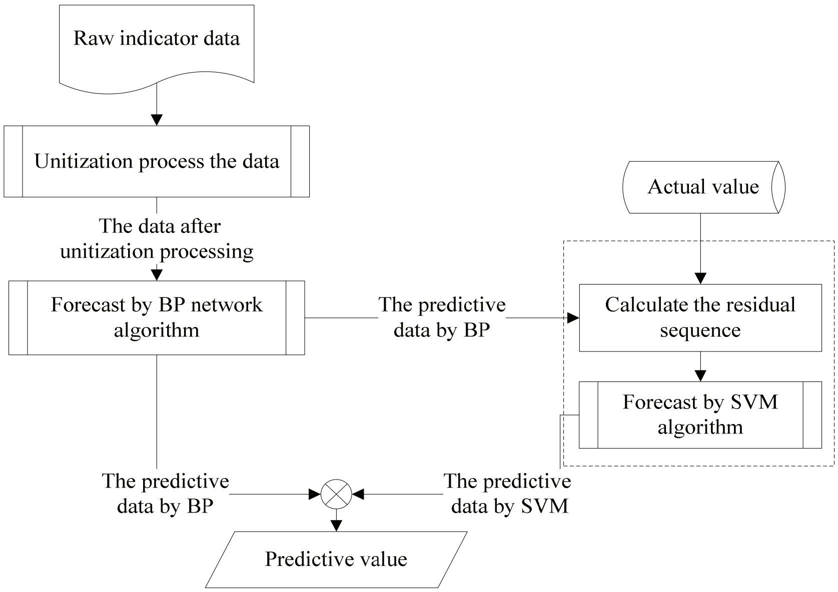


Fig. 1. Flow chart of the combined prediction algorithm.

The complete process of the proposed combined prediction algorithm is shown in Fig. 1. First, the algorithm obtains the relevant preliminary data according to the establishment of the predictive index system of foreign trade container volumes, and normalizes the preliminary data. Then, it predicts and analyzes the data from preprocessing by the BP neural network model, and acquires the preliminary prediction data. It uses the difference between the preliminary data and the BP network prediction data as a new sequence, i.e., the residual sequence. The algorithm analyzes the residual sequence by SVM, and obtains the revised prediction residual values. Finally, it obtains the final prediction results by adding the prediction data from the BP neural network and the residual values predicted by the SVM model. We use a combined prediction model that corrects residual error.

3.2 The Algorithm Design

Studies show that the BP neural network model is effective with training data values between 0 and 1. To improve the learning speed of the model, we normalize the input data according to formula (3-1).

$$x_i' = \frac{x_i - x_{min}}{x_{max} - x_{min}} \tag{3-1}$$

where x_i is the preliminary data, x_i' is the data after normalized processing, x_{min} and x_{max} are the minimum and maximum values of each variable.

The data x_i' is used as input data in the BP neural network model to generate the preliminary predicted data $\widehat{y_i}$. In this process, we set the initial weights and threshold values at a small random array, the training times at 50 and the error function as ε. For the input matrix x_{ki}' $(k = 1,2,\dots,R; i = 1,2,\dots,M)$, R and M are the numbers of rows and columns of the input matrix, respectively. The prediction output y_k can be obtained through the neural network according to the following nonlinear activation function.

$$y_k = f(net_k) = \frac{1}{1+\exp(-net_k)} \tag{3-2}$$

where net_k is the input value of the node k in the output layer. $net_k = \sum_{k=1}^{L} \omega_{jk} x_{jk}' + \theta_k$, L is the total number of nodes in the output layer, ω_{jk} is the weight of the output layer, and θ_k is the threshold value of node k. In the BP neural network data training process, it is necessary to amend the error value of the output layer and the hidden layer constantly until the prediction results satisfy the accuracy requirements, i.e. for the error function to achieve $E_p \leq \varepsilon$.

$$E_p = \frac{1}{2}\sum_{k=1}^{L}(y_{pk} - a_{pk})^2 \tag{3-3}$$

where y_{pk} is the expected output value of the node k in the output layers and a_{pk} is the output value of node k from the output layers. The weight values (ω_{ij} and ω_{jk}) of the hidden layer and the output layer can be amended by formulas (3-4) and (3-5).

$$\omega_{ij}(k+1) = \omega_{ij}(k) + \eta_j \delta_j a_j + a_j(\omega_{ij}(k) - \omega_{ij}(k-1)) \tag{3-4}$$

$$\omega_{jk}(k+1) = \omega_{jk}(k) + \eta_k \delta_k a_k + a_k(\omega_{jk}(k) - \omega_{jk}(k-1)) \tag{3-5}$$

where $\delta_j = a_j(1-a_j)\sum_{k=1}^{L}\delta_k\omega_{jk}$ is the error value from the hidden layer, δ_k ($\delta_k = y_k(1-y_k)(y_{pk}-y_k)$, $k = 1,2,\dots,L$) is the error value from the output layer, η_j and η_k are the training speed thresholds, a_j and a_k are values from the hidden layer and output layer, respectively.

We combine the actual data with the BP neural network predicted value to generate a new residual sequence, represented as ζ_k ($\zeta_k = y_k - \widehat{y_k}$). According to the SVM prediction model in formula (3-6), the amended residual sequence ζ_k' can be calculated.

$$f(\zeta_k) = \omega^T\Phi(\zeta_k) + b \tag{3-6}$$

where ω is a weight vector and b is the depth offset.

The research adopts the ω-non-sensitive loss function, and establishes the model by cross-verifying the training sets. The function can be represented as

$$L_\omega = \begin{cases} |f(\zeta_k) - \zeta_k'| - \varepsilon & |f(\zeta_k) - \zeta_k'| \geq \varepsilon \\ 0 & |f(\zeta_k) - \zeta_k'| < \varepsilon \end{cases} \tag{3-7}$$

To obtain a better generalization ability in the training sets of the SVM prediction model, minimize the empirical prediction inaccuracy risk and the reduce the computational complexity, we introduce the Lagrange multiplier into the SVM:

$$f(\zeta_k) = \sum_{k=1}^{n} a_k^* k(\zeta_k, \zeta_k') + b \tag{3-8}$$

where $k(\zeta_k, \zeta_k')$ is kernel function of SVM and a_k^* is the Lagrange multiplier.

We follow the existing research and use the radial basis kernel function [13,16] (as presented in formula (3-9)) to establish the SVM prediction model.

$$k(\zeta_k, \zeta_k') = \exp(-\frac{||\zeta_k - \zeta_k'||^2}{\sigma^2}) \tag{3-9}$$

Finally, we obtain the final prediction result $\hat{y} = \widehat{y_k} + \zeta_k'$, where $\widehat{y_k}$ is calculated by the BP neural network model and ζ_k' is the amended residual value estimated by SVM.

4. Experiments and Analysis

4.1 Indexes for Foreign Trade Container Volume Prediction

Based on the analysis of factors influencing the volume of foreign trade containers, we select the regional GDP, total volume of import and export trade, total investment in fixed assets, container throughput, container loading, the rate of container cargo loading and the rate of foreign trade goods suitable for containers to check the effectiveness of the proposed approaches.

Proper indexes selection is conducted with the help of the gray relational analysis method, which contain three processes:

(1) The raw data is pre-treated by average transforming, according to the following formula:

$$X_i' = {}^{X_i}/_{X_1} = \left(X_i'(1), X_i'(2), \dots, X_i'(n)\right),\ i = 1,2,\dots,m \tag{4-1}$$

(2) Figure out the absolute value $\Delta_{0i}(t_j)$ between each sequence and its sub-sequence at each time point, and calculate the relationship coefficient between the maximum value and the minimum value of $\Delta_{0i}(t_j)$ by formula (4-2).

$$\Delta_{0i}(t_j) = \frac{\Delta_{min} - \Delta_{max}}{\Delta_{0i}(t_j) + \Delta_{max}} \tag{4-2}$$

where Δ_{max} is the maximum of $|X_i - X_0|$, Δ_{min} is the minimum of $|X_i - X_0|$, and $\Delta_{0i}(t_j)$ is the value of $|X_i - X_0|$ at the time t_j.

(3) Calculate the average of all the relationship coefficients to conduct gray correlation analysis, and choose the indexes correspondingly according to the gray correlation values.

With the help of MATLAB, we calculate the gray relational degree of the pre-selected indexes and find their gray relational degree in descending order as follows: container throughput, total volume of import and export trade, regional GDP, container loading, total investment in fixed assets, the rate of foreign trade goods suitable for containers and the rate of container cargo loading. Therefore, we select the top five indexes to predict the volume of foreign trade containers.

According to the result of the analysis of the gray relational degree, the foreign trade container volume (ten thousand TEU) is set as Y, the regional GDP (¥100 million) is set as X_1, the total volume of import and export trade ($ billion) is set as X_2, the total investment in fixed assets (¥100 million) is set as X_3, the container loading (ten thousand ton) is set as X_4 and the container throughput (ten thousand TEU) is set as X_5. Relevant data for Ningbo and Wenzhou in 2002–2014 are selected for simulation and verification. The data for 2002–2009 serve as the training data set and are used for optimization and establishment of the model's parameters; the related data from 2010 to 2014 are used to examine the accuracy and adjust the values of parameters in the proposed prediction models; finally, the model with the optimized parameter values is used to predict the volume of foreign trade containers for the two cities during 2015–2019.

4.2 Primary Data Acquisition and Preprocessing

To evaluate the effectiveness of our methods, we select and establish the foreign trade container volume related indexes from publicly available statistical yearbook (as shown in Table 1).

4.3 Prediction with Combined Models

In MATLAB, we establish a BP neural network model with 20 nerve cells in the hidden layer, 5 nerve cells in the input layer and 1 nerve cell in the output layer. The normalized data indexes X_1, X_2, X_3, X_4, X_5 (see Table 2) are used as the input training dataset to predict the Y values and get the residual sequence accordingly.

The residual sequence is amended by using the SVM toolbox of MATLAB, with a radial basis kernel function. The final prediction results are obtained by adding the prediction data of the BP neural network and the residual sequence after correcting.

Table 1. Foreign trade container volume and related factors in Ningbo and Wenzhou 2002–2014

Region	Year	X_1	X_2	X_3	X_4	X_5	Y
Ningbo	2002	1453.34	122.73	601.27	922.79	185.86	156.68
	2003	1749.27	188.09	740.92	1408.12	277.22	239.28
	2004	2109.45	261.12	1026.64	2057.35	400.50	345.02
	2005	2447.32	334.94	1268.55	2714.81	520.80	453.89
	2006	2874.42	422.12	1413.00	3940.29	706.80	617.01
	2007	3418.57	564.99	1486.54	4450.74	935.00	815.90
	2008	3946.52	678.40	1610.86	5155.47	1084.60	969.39
	2009	4334.33	608.13	1860.45	5446.40	1042.30	911.60
	2010	5181.00	829.04	2034.99	6572.16	1300.40	1143.78
	2011	6074.94	981.87	2385.50	8933.93	1451.20	1266.71
	2012	6601.21	965.73	2901.42	9711.34	1567.10	1336.23
	2013	7164.51	1003.29	3422.95	10395.44	1677.40	1416.16
	2014	7610.28	1046.50	3989.46	11359.65	1869.99	1562.37
Wenzhou	2002	1052.35	34.54	296.02	32.65	13.34	6.23
	2003	1212.49	44.75	351.54	46	15.85	6.50
	2004	1388.91	59.67	398.93	60.38	21.30	7.08
	2005	1590.82	78.60	465.92	61.15	23.02	7.33
	2006	1826.92	98.94	557.88	71.17	28.35	5.59
	2007	2146.62	122.48	640.59	78.12	35.10	9.25
	2008	2407.46	139.92	655.84	44.1	38.10	9.87
	2009	2520.51	132.79	724.48	120.28	38.80	9.64
	2010	2918.82	170.94	802.00	142.01	42.08	9.84
	2011	3407.97	215.72	1540.31	288.29	46.66	13.42
	2012	3670.56	204.38	2110.34	282.87	51.75	13.16
	2013	4024.50	206.02	2618.16	229.12	57.27	14.29
	2014	4303.05	207.82	3052.81	235.99	60.08	14.99

The data are from the Ningbo Statistical Yearbook, the Wenzhou Statistical Yearbook, and the China's Ports-of-entry Yearbook in 2002–2014. According to formula (3-1), the data in Table 1 can be normalized (as shown in Table 2).

Table 2. Foreign trade container volume and related factors after normalization

Region	Index	X_1	X_2	X_3	X_4	X_5	Y
Ningbo	2002	0	0	0	0	0	0
	2003	0.05	0.07	0.04	0.05	0.05	0.06
	2004	0.11	0.15	0.13	0.11	0.13	0.13
	2005	0.16	0.23	0.20	0.17	0.20	0.21
	2006	0.23	0.32	0.24	0.29	0.31	0.33
	2007	0.32	0.48	0.26	0.34	0.44	0.47
	2008	0.40	0.60	0.30	0.41	0.53	0.58
	2009	0.47	0.53	0.37	0.43	0.51	0.54
	2010	0.61	0.76	0.42	0.54	0.66	0.7
	2011	0.75	0.93	0.53	0.77	0.75	0.79
	2012	0.84	0.91	0.68	0.84	0.82	0.84
	2013	0.93	0.95	0.83	0.91	0.89	0.9
	2014	1	1	1	1	1	1
Wenzhou	2002	0	0	0	0	0	0
	2003	0.05	0.06	0.02	0.05	0.05	0.07
	2004	0.1	0.14	0.04	0.11	0.17	0.1
	2005	0.17	0.24	0.06	0.11	0.21	0.16
	2006	0.24	0.36	0.09	0.15	0.32	0.19
	2007	0.34	0.49	0.12	0.18	0.47	0
	2008	0.42	0.58	0.13	0.04	0.53	0.39
	2009	0.45	0.54	0.16	0.34	0.54	0.46
	2010	0.57	0.75	0.18	0.43	0.61	0.45
	2011	0.72	1	0.45	1	0.71	0.83
	2012	0.81	0.94	0.66	0.98	0.82	0.81
	2013	0.91	0.95	0.84	0.77	0.94	0.93
	2014	1	0.96	1	0.8	1	1

4.4 Comparison and Analysis of the Predicted Results

The research conducts a comparison of predicted foreign trade container volume values from the BP neural network, SVM and the combined approach for Ningbo and Wenzhou in 2010–2014, respectively (as shown in Table 3).

According to the data in Table 3, the volume of foreign trade containers in Ningbo increases steadily during 2010–2014. By contrast with Ningbo, the volume of foreign trade containers in Wenzhou increases suddenly between 2010 and 2011, but in the following 2 years it comes down steadily. Also, it can be found in Figs. 2 and 3 that the predicted values from the BP neural network model, SVM and the combined model generally reflect these tendencies. However, the foreign trade container volume values from the prediction results of the SVM and the combined prediction model are closer to the actual values than those of the BP neural network method. One reason may be that the BP neural network model obtains the results by repeated training, but the precision and frequency of the training is set by human agents. If the value is not properly set, the error may be very large. The combined prediction model is based on the prediction of the BP neural network and the residual sequence amended by SVM, which improve the precision of the prediction effectively, and can obtain more accurate results.

Table 3. Predicted results and error analysis of different methods (unit: ten thousand TEU)

Region	Year	Actual value	BP prediction value	Relative error of BP prediction (%)	SVM prediction value	Relative error of SVM prediction (%)	Combined method prediction value	Relative error of the combined prediction (%)
Ningbo	2010	1143.78	1179.60	3.13	1161.73	1.57	1155.79	1.05
	2011	1266.71	1315.30	3.84	1287.14	1.61	1279.63	1.02
	2012	1336.23	1366.20	2.24	1347.07	0.81	1347.99	0.88
	2013	1416.16	1447.00	2.18	1396.66	1.38	1399.17	1.20
	2014	1562.37	1522.37	2.56	1601.59	2.51	1586.59	1.55
Wenzhou	2010	9.84	9.99	1.52	9.70	1.41	9.71	1.31
	2011	13.42	13.42	1.78	13.70	2.08	13.60	1.32
	2012	13.16	13.63	3.59	13.33	1.31	13.29	1.02
	2013	14.29	14.83	3.80	14.14	1.04	14.14	1.06
	2014	14.99	15.21	1.44	15.32	2.19	15.14	1.01

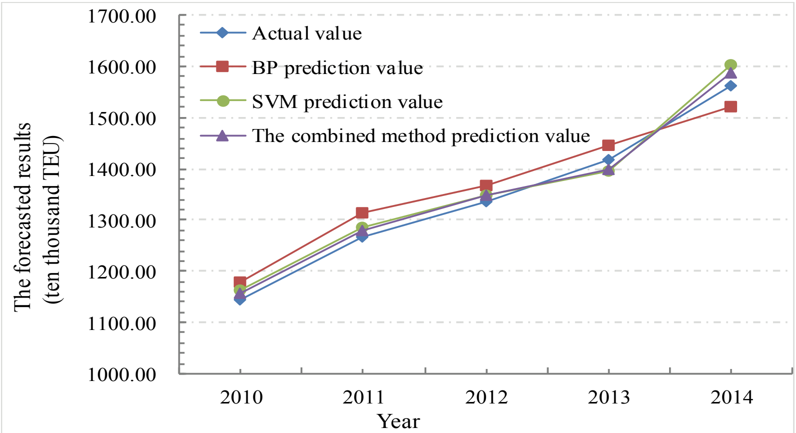


Fig. 2. Predicted value of foreign trade containers volume in Ningbo based on three prediction methods.

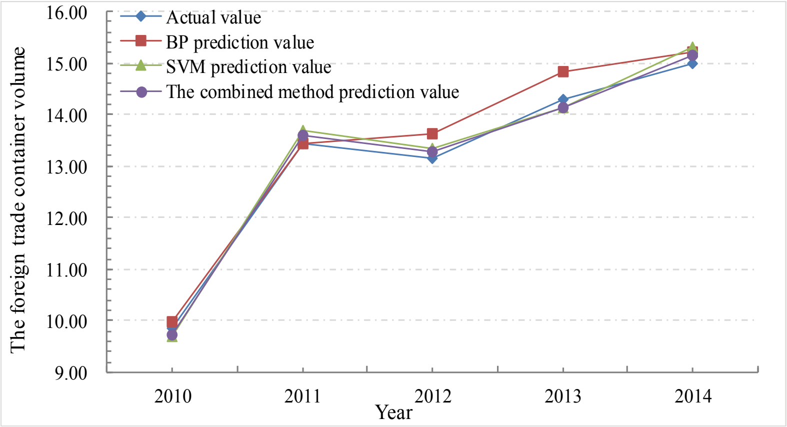


Fig. 3. Predicted value of foreign trade container volume in Wenzhou based on three prediction methods.

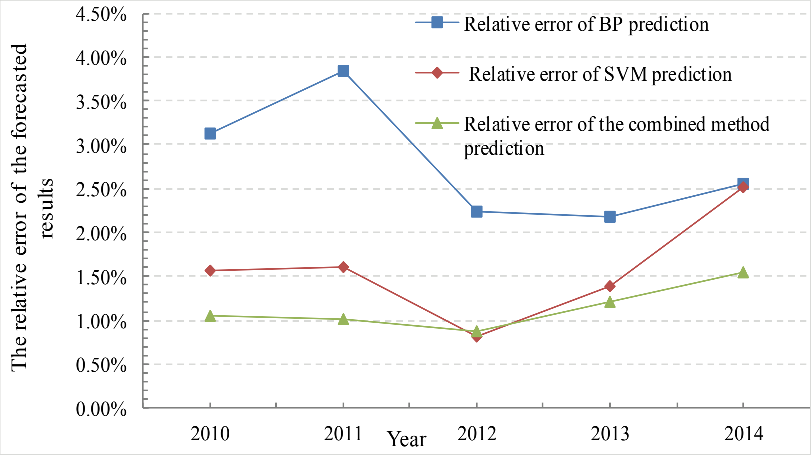


Fig. 4. Relative error of the predicted results of Ningbo from three prediction models.

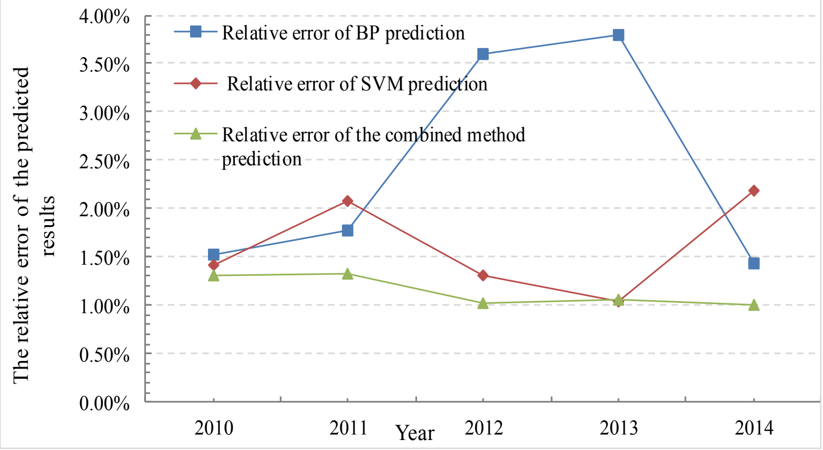


Fig. 5. Relative error of the predicted results of Wenzhou from three prediction models.

Figs. 4 and 5 plot the relative errors of the predicted results for Ningbo and Wenzhou from the three prediction models. They imply that the relative error of the combined prediction model is smaller than the other two single prediction models, and the relative error of the BP's predicted value is higher than the actual value. As can be found from the data in Table 3, the relative errors of SVM and the combined prediction model are less than 3.0% and 1.6%, respectively. All these results indicate the superiority of the joint prediction method.

4.5 Foreign Trade Container Volume Prediction in 2015–2019

The real data experiment in the previous section proves that the degree of fitting of the prediction results from the joint prediction model that combines the BP neural network with SVM is higher than the other two methods predicting singly. Therefore, we employ the combined model to predict the foreign trade container volumes for Ningbo and Wenzhou in 2015–2019. The predicted results are shown in Table 4. The overall trend of the foreign trade container volume and the yearly growth ratio for the two cities are plotted in Figs. 6 and 7.

Based on the prediction, we can draw a general conclusion that the foreign trade container volumes in both Ningbo and Wenzhou will continue to increase in the next 5 years. Additionally, the yearly growth rate of foreign trade container volume for Ningbo will be faster than for Wenzhou in 2015–2019.

Table 4. Predicted values of foreign trade container volume in Ningbo and Wenzhou (unit: ten thousand TEU)

	2015	2016	2017	2018	2019
Ningbo	1586.95	1579.15	1627.51	1691.57	1759.49
Wenzhou	14.85	14.21	15.21	15.7	17.35

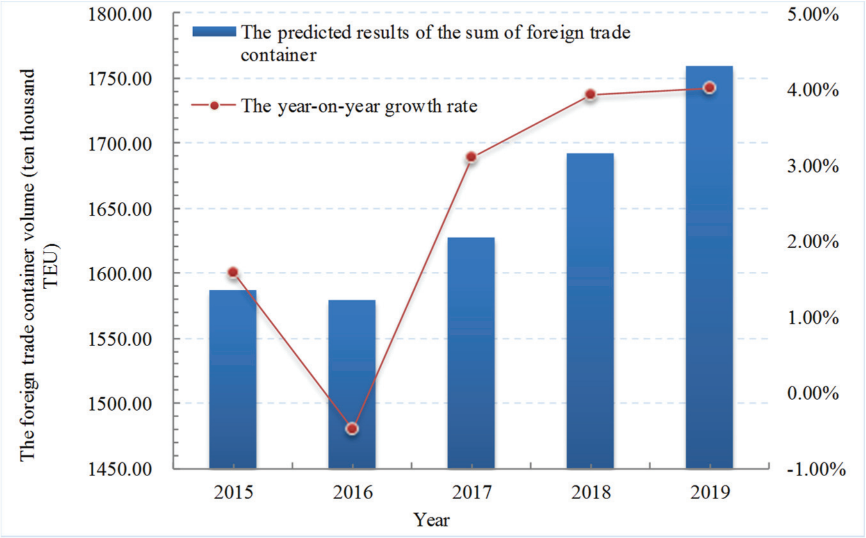


Fig. 6. Predicted results of the foreign trade container volume in Ningbo.

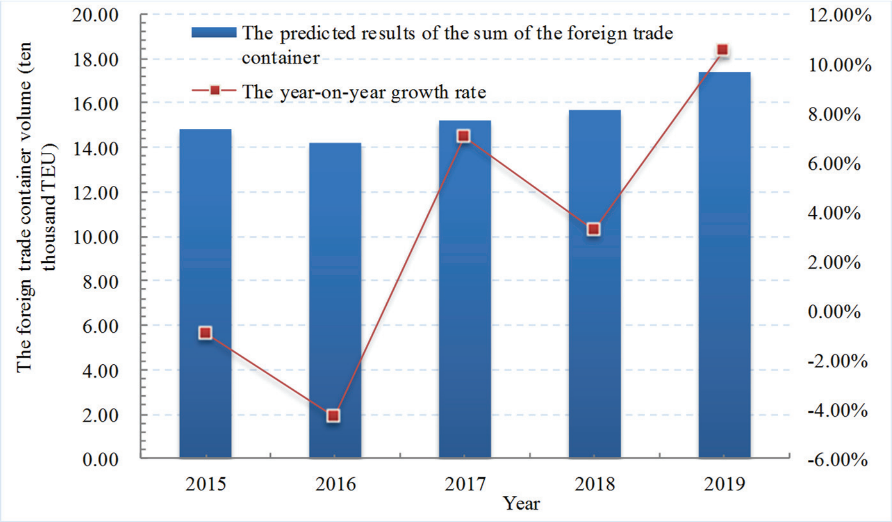


Fig. 7. Predicted results of the foreign trade container volume in Wenzhou.

5. Conclusion

In this paper, we study the influencing factors for the foreign trade container volume and establish a joint prediction method that combines a BP neural network model and SVM. Based on gray relational analysis, the top five influencing factors are selected to predict the foreign trade container volume in Ningbo and Wenzhou. The proposed joint prediction model uses SVM to correct the residual sequence after initial prediction by the BP neural network model and real statistical yearbook data for the two cities in 2010–2014 are selected to compare the efficiency of the prediction methods. In our prediction experiment, the relative error of the proposed combined prediction method is much lower than the other single models. This result suggests an effective and potential application value in logistics-demand predicting. Based on the proposed prediction approach, we find that the foreign trade container volume in both Ningbo and Wenzhou will increase steadily in 2015–2019, and the yearly growth rate of Ningbo will be faster than Wenzhou.

Acknowledgement

This work was supported by the Natural Science Foundation of Zhejiang (No. LY16G020012), the Major Research Projects of Humanities and Social Sciences in Colleges and Universities of Zhejiang (No. 2014GH015), the Open Research Funding Program of the Key Laboratory of Geographic Information Science (Ministry of Education), East China Normal University (No. KLGIS2014A0l), the Zhijiang Youth Action Project: study on mobile e-commerce recommendation (No. G306), the Zhejiang Association for Business Economics project (No. 2016SJYB01), the key project of Ningbo Education Science Planning (No. 2017YZD010), and the Modern Port Service Industry and Culture Research Center of the Key Research Base of Philosophy and Social Sciences of Zhejiang Province.

References

[1] S. Makridakis and R. L. Winkler, "Averages of forecasts: Some empirical results," *Management Science*, vol. 29, no. 9, pp. 987-996, 1983.

[2] G. Chen and Z. Yang, "Optimizing time windows for managing export container arrivals at Chinese container terminals," *Maritime Economics & Logistics*, vol. 12, no. 1, pp. 111-126, 2010.

[3] X. Hao and R. Suo, "The application of combination forecasting model in forecasting the total power of agricultural machinery in Heilongjiang Province," *Asian Agricultural Research*, vol. 7, no. 5, pp. 25-28, 2015.

[4] C. C. Chou, C. W. Chu, and G. S. Liang, "A modified regression model for forecasting the volumes of Taiwan's import containers," *Mathematical and Computer Modelling*, vol. 47, no. 9-10, pp. 797-807, 2008.

[5] H. S. Hwang, S. T. Bae, and G. S. Cho, "Container terminal demand forecasting framework using fuzzy-GMDH and neural network method," in *Proceedings of the 2nd International Conference on Innovative Computing, Information and Control*, Kumamoto, Japan, 2007.

[6] W. Y. Peng and C. W. Chu, "A comparison of univariate methods for forecasting container throughput volumes," *Mathematical and Computer Modelling*, vol. 50, no. 7-8, pp. 1045-1057, 2009.

[7] V. Gosasang, W. Chandraprakaikul, and S. Kiattisin, "A comparison of traditional and neural networks forecasting techniques for container throughput at Bangkok port," *The Asian Journal of Shipping and Logistics*, vol. 27, no. 3, pp. 463-482, 2011.

[8] V. Gosasang, W. Chandraprakaikul, and S. Kiattisin, "An application of neural networks for forecasting container throughput at Bangkok port," in *Proceedings of the World Congress on Engineering*, London, UK, 2010, pp. 1-5.

[9] J. W. Chan and T. K. Tong, "Multi-criteria material selections and end-of-life product strategy: Grey relational analysis approach," *Materials & Design*, vol. 28, no. 5, pp. 1539-1546, 2007.

[10] F. L. Chen and T. Y. Ou, "Gray relation analysis and multilayer functional link network sales forecasting model for perishable food in convenience store," *Expert Systems with Applications*, vol. 36, no. 3, pp. 7054-7063, 2009.

[11] S. Yu, K. Zhu, and F. Diao, "A dynamic all parameters adaptive BP neural networks model and its application on oil reservoir prediction," *Applied Mathematics and Computation*, vol. 195, no. 1, pp. 66-75, 2008.

[12] C. Dong, X. Dong, J. Gehman, and L. Lefsrud, "Using BP neural networks to prioritize risk management approaches for China's unconventional shale gas industry," *Sustainability*, vol. 9, article no. 979, 2017.

[13] E. Byvatov, U. Fechner, J. Sadowski, and G. Schneider, "Comparison of support vector machine and artificial neural network systems for drug/nondrug classification," *Journal of Chemical Information and Computer Sciences*, vol. 43, no. 6, pp. 1882-1889, 2003.

[14] P. S. Freitas and A. J. Rodrigues, "Model combination in neural-based forecasting," *European Journal of Operational Research*, vol. 173, no. 3, pp. 801-814, 2006.

[15] Z. Xiao, S. J. Ye, B. Zhong, and C. X. Sun, "BP neural network with rough set for short term load forecasting," *Expert Systems with Applications*, vol. 36, no. 1, pp. 273-279, 2009.

[16] C. C. Chang and C. J. Lin, "LIBSVM: a library for support vector machines," *ACM Transactions on Intelligent Systems and Technology*, vol. 2, no. 3, article no. 27, 2011.

[17] G. Xie, S. Wang, Y. Zhao, and K. K. Lai, "Hybrid approaches based on LSSVR model for container throughput forecasting: a comparative study," *Applied Soft Computing*, vol. 13, no. 5, pp. 2232-2241, 2013.

[18] P. M. Schulze and A. Prinz, "Forecasting container transshipment in Germany," *Applied Economics*, vol. 41, no. 22, pp. 2809-2815, 2009.

[19] J. K. Kim, J. Y. Pak, Y. Wang, S. I. Park, and G. T. Yeo, "A study on forecasting container volume of port using SD and ARIMA," *Journal of Navigation and Port Research*, vol. 35, no. 4, pp. 343-349, 2011.

[20] W. Y. Peng, "The comparison of the seasonal forecasting models: a study on the prediction of imported container volume for international container ports in Taiwan," *Maritime Quarterly*, vol. 25, no. 2, pp. 21-36, 2006.

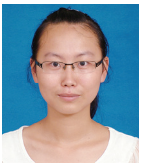
[21] C. I. Liu, H. Jula, and P. A. Ioannou, "Design, simulation, and evaluation of automated container terminals," *IEEE Transactions on Intelligent Transportation Systems*, vol. 3, no. 1, pp. 12-26, 2002.

[22] R. Diaz, W. Talley, and M. Tulpule, "Forecasting empty container volumes," *The Asian Journal of Shipping and Logistics*, vol. 27, no. 2, pp. 217-236, 2011.

[23] F. M. Tsai and L. J. Huang, "Using artificial neural networks to predict container flows between the major ports of Asia," *International Journal of Production Research*, vol. 55, no. 17, pp. 5001-5010, 2017.

[24] A. Huang, Z. Zhang, X. Shi, and G. Hua, "Forecasting container throughput with big data using a partially combined framework," in *Proceedings of the International Conference on Transportation Information and Safety (ICTIS)*, Wuhan, China, 2015, pp. 641-646.

[25] Q. Wu, "Power load forecasts based on hybrid PSO with Gaussian and adaptive mutation and Wv-SVM," *Expert Systems with Applications*, vol. 37, no. 1, pp. 194-201, 2010.



Min-jie Ding https://orcid.org/0000-0001-7698-4075

She is postgraduate of Zhejiang Wanli University. At present her research direction is the application of logistics information technology.

Shao-zhong Zhang https://orcid.org/0000-0002-4345-4171

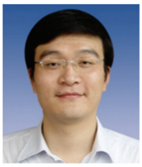
He is a professor in the Faculty of Information and Intelligence Engineering School in Zhejiang Wanli University. Also, he is research fellow of the Electronic Services Research Center of Zhejiang University and Ningbo Institute of Electronic Services. He received his B.S. in world economy from Nankai University in 1999. In 2004, he got his Ph.D. in computer application technology from Dalian University of Technology. He has published two books, more than 80 articles. At present, his research interests include data mining and knowledge discovery, sentiment analysis, big data mining, and e-commerce and business intelligence.

Hai-dong Zhong https://orcid.org/0000-0002-5549-412X

He is an associate professor in the Faculty of Logistics and E-commerce School in Zhejiang Wanli University. He received his B.S. in computer science and technology in 2004 and his Ph.D. in cartography and geography information system from East China Normal University in 2011. At present, his main research interest is in mobile e-commerce, personalized recommendation and business intelligence.

Yao-hui Wu https://orcid.org/0000-0003-1347-0442

He is an associate professor in the Faculty of Information and Intelligent Engineering School in Zhejiang Wanli University. He received his B.S. in communication engineering from Beijing University of Posts and Telecommunications, China in 2004, and received his Ph.D. in communication engineering from Ningbo University, China in 2018. At present, his main research interest is in wireless communication, wireless networking and information fusion.



Liang-bin Zhang https://orcid.org/0000-0003-0783-7316

He is an associate professor in the Faculty of Big Data and Software Engineering School in Zhejiang Wanli University. He received his B.S. in computer science and application from Hangzhou University of Electronic Science and Technology, China in 2006. At present, his main research interest is in cloud computing, edge computing, system integration, image coding, etc.