Hindawi
Discrete Dynamics in Nature and Society
Volume 2022, Article ID 7029980, 9 pages
https://doi.org/10.1155/2022/7029980

Research Article

Algorithm Design of Port Cargo Throughput Forecast Based on the ES-Markov Model

Yan Yi [1] and Seyed Taha Seyed Sadr [2]

[1] *School of International Cruise and Yacht, Guangzhou Maritime University, Guangdong, Guangzhou 510725, China*
[2] *Department of Industrial Engineering, South Tehran Branch, Islamic Azad University, Tehran, Iran*

Correspondence should be addressed to Yan Yi; yiyan456789@126.com and Seyed Taha Seyed Sadr; sts.sadr@srbiau.ac.ir

Received 10 July 2022; Revised 28 July 2022; Accepted 12 August 2022; Published 26 September 2022

Academic Editor: Reza Lotfi

At present, the existing prediction algorithm of a port cargo throughput neglects the correction of the initial value of the cargo series data model, which leads to a large error in a port cargo throughput prediction. Therefore, a prediction algorithm of a port cargo throughput based on the ES-Markov model is designed. A decompose function is used to decompose the time series of a port cargo throughput, and the trend elements of a port cargo throughput are divided into long-term trend, seasonal trend, fluctuation trend, and irregular trend. In this study, the ES-Markov model is introduced, and the initial prediction is obtained by using the cubic exponential smoothing method, and the state transition matrix is obtained by the Markov principle. Based on the results of the time-series analysis and the ES-Markov model, the prediction algorithm of a port cargo throughput is designed. In the experimental design, the Elman neural network is used to construct an experimental sample data model. The monthly cargo throughput data of a certain port for eight months from May 2020 to December 2020 are collected and sorted according to the time series. The experimental results show that the prediction results of the proposed algorithm are closer to the actual value and the fluctuation of the prediction results is less than that of the reference.

1. Introduction

Since the beginning of the 21st century, the rapid development of economic globalization has deeply affected the development of the production and transportation industries, and regional economic integration has been developing with the tide. As an important economic and transportation hub, the central strategic position of ports has become prominent [1–5]. Historically, the first generation of ports has been an important transport hub, with its main functions being the conversion of means of transport and the transfer of goods, where large quantities of goods are concentrated, and the movement of goods is bound to promote economic development; the second generation of ports, in turn, has added commercial services to the first generation, thus spawning new processing industries and further promoting industrial development, and the third generation of ports, in turn, has eliminated the obvious monopoly of information between cities, cargo owners, and consumers, but has made their links more frequent, and port services have not been limited to trans-shipment of goods, but have increased services such as real-time inquiries about cargo information and commodity distribution, at a time when ports have assumed a central position in international logistics and promoted the development of international trade [6–11]. So far, the port has developed to the fourth generation, the port development mode is the most efficient, that is, the supply chain mode serving the integration of trade, manufacturing industry, and logistics. Nowadays, the aim of intelligent port is to improve the efficiency of port operation and management, which is also a test of port construction and management [12–16]. The accurate forecast of a cargo throughput provides a basis for the planning, deployment, and reasonable allocation of tasks in advance, avoids the occurrence of a cargo backlog in the port, does not affect the delivery of goods and customer satisfaction, and fully improves the operating efficiency of the port, forming a virtuous circle [22–24]. Therefore, accurate and reasonable forecast of a port cargo throughput is very important for port layout and even transformation and upgrading.

Li et al. [25] argue that the ant colony algorithm is used to optimize the initial weight and threshold of back-propagation neural network, and a prediction model is established to predict the port cargo throughput. The ant colony algorithm has the characteristics of global search ability, distributed computing, and strong robustness. It is conducive to accelerate the convergence speed of back-propagation neural network, avoid the problem of easy falling into local extremum, and improve the modeling accuracy.

Chen et al. [26] studied and analyzed the main index factors affecting the port throughput. On the basis of the SVM prediction method, the genetic algorithm (GA) and grid search algorithm (GS) are used to optimize and improve the main parameters of the SVM model. The prediction results of the GA-SVM and GS-SVM models are based on the SVM prediction method, and the genetic algorithm and GS method are used to optimize and improve the main parameters of the SVM model; the prediction results of genetic support vector machine and GS support vector machine are tested by MSE and R2. The improved SVM model is a new port throughput prediction method based on the current research results, which can be popularized and applied in the overall port planning.

Wang et al. [27] proposed a dynamic three-parameter grey prediction model. Firstly, the model parameters are estimated directly by difference equation. Then, the TPGM (1, 1) prediction model is constructed based on the model parameter values. Finally, combined with the idea of metabolism, the old data are discarded and the predicted value is added as a new original data sequence for modeling, so as to realize the dynamic prediction of passenger throughput of civil airport.

Shankar et al. [28] used the deep learning method to predict the container throughput, and the performance of other traditional time-series methods is compared. This study uses long-term and short-term memory (LSTM) network to predict container throughput. The container throughput data of Singapore port are used for empirical analysis. The prediction performance of the LSTM model is compared with seven different time-series prediction methods: autoregressive comprehensive moving average (ARIMA), simple exponential smoothing, Holt winter, error trend seasonality, triangular regression (tbats), neural network (NN), and ARIMA + NN.

However, the above reference algorithm ignores the correction of the initial value of the cargo sequence data model, resulting in large errors in the prediction results of a port cargo throughput. Therefore, we mainly aim to design a port cargo throughput prediction algorithm based on the ES-Markov model.

2. Literature Review

Using big data, Ouyang [6] demonstrated that the selection of the data fusion for the port logistics supply chain integrated management model is rational. It suggests that the logic of the mode selection for integrated management of the port logistics supply chain is more accurate and that the capability for integrated management of the port logistics supply chain in the context of the Internet of Things is enhanced.

The gross ocean product, port cargo throughput, and container throughput in coastal areas are the three key components of Liu's grey model first-order one variable (GM [1]) model forecast of the port and marine engineering economics, which was created according to the grey theory. It will be possible to comprehend and anticipate the ports throughput accurately using the GM (1, 1) model. This study concluded by making some recommendations on how to more effectively carry out the economic growth of port and marine engineering.

In the context of a Smart Port-City, Lacalle et al. [17] suggested an IoT-based software architecture together with a methodology for designing, computing, and forecasting composite indicators that represent real-world occurrences. In their study, the framework is envisioned, developed, and applied to a genuine use case as a practical experiment. The initiative involves setting up a composite index to track traffic congestion at Thessaloniki's port-city interface (Greece). Results met expectations, were confirmed by nine scenarios, and culminated in the delivery of a practical tool that interested parties at Smart Port-Cities can be used to explore and develop policy.

Long short-term memory (LSTM) networks were used by Shankar et al. [28] to anticipate container throughput. For empirical study, the container throughput data from the Port of Singapore were used. The performance of the LSTM model was compared to that of seven other time-series forecasting techniques, including the neural network (NN), ARIMA + NN, Holt Winter's, error-trend-seasonality, trigonometric regressors (TBATS), and simple exponential smoothing. The performance of the various models was examined with regard to bias, accuracy, and uncertainty using the relative error matrix. The outcomes revealed that LSTM performed better than any other benchmark technique.

To the best of our knowledge, despite the potentials of the ES-Markov model, it has not yet been employed to design a port cargo throughput prediction algorithm and such a gap can be removed by the present study and following research.

3. Problem Statement

The port cargo throughput reflects not only a country's local economic development but also a measure of a country's financial and trade development of the key indicators. In order to accurately predict a port cargo throughput, the first task is to analyze the time series of a port cargo throughput.

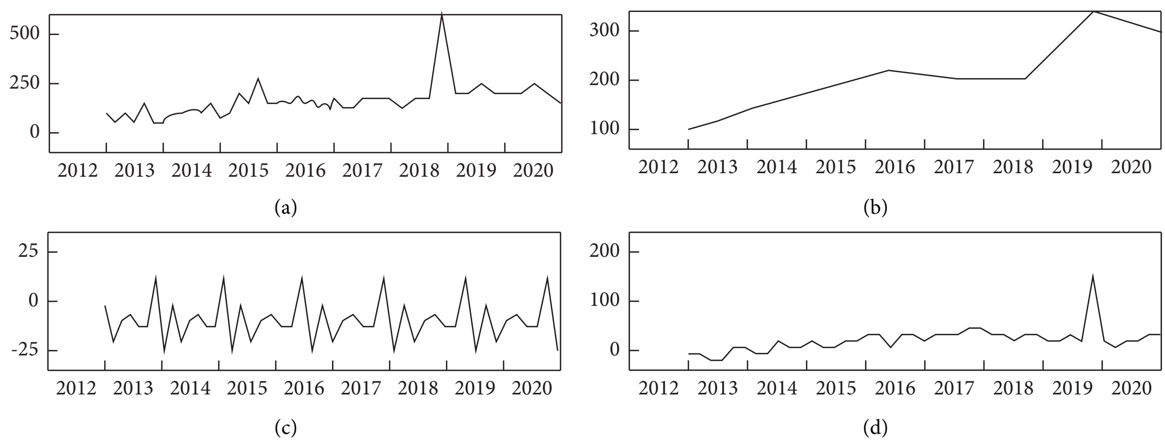

Figure 1: Time-series breakdown of a port cargo throughput.

The time-series analysis of a port cargo throughput refers to sequencing according to the generation time of a port cargo throughput data and analyzing the variation law of the port cargo throughput data. Based on this, the study provides reference for the construction of the following forecast model of a port cargo throughput [29]. Time-series analysis method is a series solution method, which combines numerical analysis, matrix theory, and many other analysis principles, and is widely used in many fields.

3.1. Time-Series Analysis of Cargo Throughput. There are many factors that affect the cargo handling capacity of the port, such as natural conditions, geographical location of the port, national regulations and policies, and economic situation. The mechanisms by which these factors work are difficult to quantify numerically, but can be fully fed back into the time series of throughput data.

In order to clearly analyze the time series of the port cargo throughput, the decomposing function is used to decompose the time series of the port cargo throughput. The throughput unit of the ordinate is 10^4 t and the abscissa is year. The exploded view is shown in Figure 1.

As shown in Figure 1, the trend components of a port cargo throughput time series are mainly divided into four categories, including long-term trend, seasonal trend, volatility trend, and irregular trend. The trend of time series of a port cargo throughput is mainly determined by the factors such as regional GDP level, economic policy, and instrument quota and shall be determined according to the actual situation [30, 31].

3.2. Design of Throughput Prediction Algorithm Based on the ES-Markov Model. The ES-Markov model [32, 33] combines the cubic exponential smoothing method with the Markov model. First, the initial prediction value is obtained by the cubic exponential smoothing method [34], and then, the state transition matrix is obtained by the Markov principle. The initial prediction value is modified to improve the prediction accuracy.

The exponential smoothing method is a special moving average method, which is characterized by assigning different weights to the previous observations, assigning larger weights to the new data, and assigning smaller weights to the old data, and the predicted values are the weighted sum of the previous observations. The exponential smoothing prediction method includes 3 methods: the first exponential smoothing method is suitable for nontrend stationary time series. the second exponential smoothing method is suitable for linear time series, and the third exponential smoothing prediction method is suitable for irregular and nonlinear time series. The cargo handling capacity of a port is influenced by the national policy, the surrounding economic development, and the natural environment, which leads to its obvious nonlinear characteristics [35–37]. Therefore, the method of exponential smoothing is used to predict the initial value. The third exponential smoothing formula is as follows:

$$\begin{cases} W_N^1 = \delta X_N + W_{N-1}^1 - \delta \cdot W_{N-1}^1, \\ W_N^2 = \delta X_N + W_{N-1}^2 - \delta \cdot W_{N-1}^2, \\ W_N^3 = \delta X_N + W_{N-1}^3 - \delta \cdot W_{N-1}^3, \end{cases} \tag{1}$$

where $N = 2, 3$, W_N^1 is the primary exponential smoothing value of the port cargo throughput in phase N, W_N^2 is the quadratic exponential smoothing value of the port cargo throughput in phase N, W_N^3 is the third exponential smoothing value of the port cargo throughput in phase N, X_N is the Nth actual data of the port cargo throughput time series, δ is the static smoothing coefficient, and $\delta \in (0, 1)$.

The predicted value of $N + m$ is as follows:

$$X_{N+m} = a + bm + cm^2, \tag{2}$$

where m is the prediction step size and the positive integers are $1, 2, 3, \ldots, n$.

The specific steps of the ES-Markov model construction are as follows.

3.2.1. Calculation Accuracy. The accuracy is the ratio of the actual value to the initial value of cubic exponential smoothing prediction, i.e.,

$$H_N = \frac{X_N}{\widehat{X_N}}. \tag{3}$$

3.2.2. Construction of State Transition Probability Matrix. The state transition probability p_{ij} is calculated as follows:

$$p_{ij} = \frac{M_{ij}}{M_i}, \quad i = 1, 2, \ldots, n;\ j = 1, 2, \ldots, n, \tag{4}$$

where p_{ij} is the probability of objective things transferring from one state to another, M_i is the number of original data in the initial state, M_{ij} is the number of original data transferred to the original state after step k, and M_i at the end of the sample sequence is not included in the formula.

3.2.3. Determining Forecast Timing Transition Status. Markov chain has no aftereffect; that is, the occurrence of transition is only related to the current state. If the predicted object is in the initial state, only line i state vector p_{ij} of the current state transition probability matrix is considered. If the probability value of column j is the largest, the predicted object is most likely to turn to the initial state at the next moment.

Based on the above analysis results of the port cargo throughput time series, the original time series is examined, and a prediction model of the port cargo throughput is established on the basis of grey system theory [38]. The specific construction process is as follows.

In order to build a high precision throughput prediction model, the first task is to verify the original time series. Set level expression to

$$\sigma(k) = \frac{x(k-1)}{x(k)}, \tag{5}$$

where $\sigma(k)$ represents the stage ratio of x and x represents the original time series.

Then, the formula of original data time series test [39] is as follows:

$$\sigma(k) \in \left(e^{-2/n+1}, e^{2/n+1}\right), \quad k = 2, 3, \ldots, n. \tag{6}$$

If the level ratio $\sigma(k)$ of the original time series satisfies formula (6), the said time series can be considered as the design data of the throughput prediction algorithm; if the level ratio $\sigma(k)$ of the original time series does not satisfy formula (6), the level ratio of the time series can be brought into a given range by means of translation transformation. The time series after translation transformation is recorded as y, and the order ratio expression is $\varphi(k)$.

Based on the above verified original time series, the throughput prediction model is generated by accumulation to make it have strong regularity. The design process of the throughput prediction algorithm is as follows:

Set the original time series set after inspection as $X(k)$, and obtain the number series $X^{(1)}(k)$ through first order accumulation. On this basis, calculate its immediate mean series as $Z^{(1)}(k)$, and then, the throughput prediction algorithm formula is as follows:

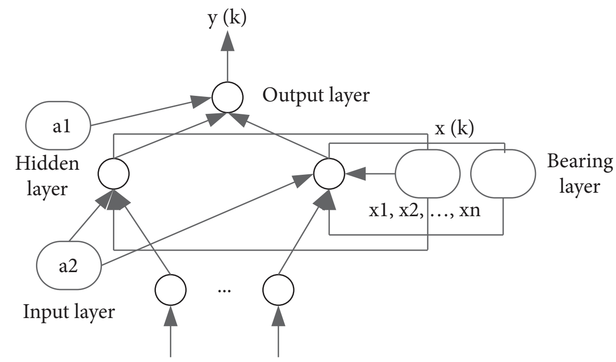

Figure 2: Elman neural network structure.

$$x^{(1)}(k+1) = \left(x^{(0)}(1) - \frac{\mu}{a}\right)e^{-ak} + \frac{\mu}{a}, \tag{7}$$

where μ represents the endogenous control grey number, reflecting the data change relationship [12, 35, 40–42], which is determined by the time series and its adjacent mean series, and a represents the development grey number, reflecting the development trend of sequence $X^{(1)}(k)$ [43].

4. Results

4.1. Sample Data Construction Based on Elman Neural Network. Elman neural network is divided into four layers. In addition to the common input layer, hidden layer, and output layer, there is a special receiving layer. Its structure is shown in Figure 2.

It can be seen from Figure 1 that the structural connection mode of the network input layer, hidden layer, and output layer is similar to the common feedforward neural network (such as the BP neural network). Elman neural network is special in that it adds a receiving layer, which is used to remember and store the output data of the hidden layer at the previous time and return it to the network input, which enhances the ability of the neural network to process dynamic information. Referring to the structural model of Elman neural network in Figure 1, the input and output relationship is shown in equations (8) to (10)as follows:

$$x(k) = f\left[\mu^1 x_c(k) + \mu^2 x_c(k-1)\right], \tag{8}$$

$$x_c(k) = x(k-1), \tag{9}$$

$$y(k) = g\left[\mu^3 x_c(k)\right], \tag{10}$$

where y, x, μ, and x_c are output layer vector, middle layer vector, input vector, and feedback vector, respectively, μ^1 is the connection weight from the receiving layer to the hidden layer, μ^2 is the connection weight from the input layer to the hidden layer, μ^3 is the connection weight from the hidden layer to the output layer, $f(\cdot)$ is the transfer function of the hidden layer, $g(\cdot)$ is the transfer function of the output layer, and k is the current time.

According to the China Port Network, the monthly cargo throughput data of a certain port for eight months from May 2020 to December 2020 are collected and sorted

Table 1: Cargo throughput of a port in 2020/10^4 t.

Month	Throughput	Month	Throughput
1	8904	7	8892
2	7820	8	8950
3	9653	9	9320
4	8702	10	9165
5	9120	11	8730
6	9034	12	8925

Table 2: Sample data construction method.

Input sample						Output sample
2020–01	2020–02	2020–03	2020–04	2020–05	2020–06	2020–07
2020–02	2020–03	2020–04	2020–05	2020–06	2020–07	2020–08
2020–03	2020–04	2020–05	2020–06	2020–07	2020–08	2020–09
2020–04	2020–05	2020–06	2020–07	2020–08	2020–09	2020–10
2020–05	2020–06	2020–07	2020–08	2020–09	2020–10	2020–11
2020–06	2020–07	2020–08	2020–09	2020–10	2020–11	2020–12

according to the time series. In order to make full use of the data, improve the forecast precision of the port cargo throughput and serve port construction better, the sample data of Elman neural network is constructed by recursively forecasting the throughput data of the next month for 8 consecutive months; that is, there are 6 input nodes and 1 output node of the neural network. Taking the monthly cargo throughput data of a port in a city in 2020 as an example, the original data are shown in Table 1, and the construction method is shown in Table 2.

Based on the data of the port cargo throughput from May 2020 to December 2020, a set of sample data can be constructed. Among them, the latter five groups of data, namely, the cargo throughput data of a certain port from July to December 2020, are used as the test data of the neural network, and the former one is used as the training data of the neural network. At the same time, in order to ensure the fast convergence of neural network, training data and test data are normalized. Before the prediction of the port cargo throughput, according to the time characteristics of the port throughput data and many experiments, the neural network structure is determined as the input layer of 6 neurons, the output layer of 1 neuron, and the hidden layer of 7 neurons. At the same time, in network training, the hidden layer, the output layer, and the training function use tansig function, purelin function, and trainlm function, respectively, while the learning function of weights and thresholds use learngdm, which drives the term.

4.2. Analysis of Experimental Results. Elman neural network is realized by MATLAB simulation. At the same time, 69 groups of cargo throughput data of Ningbo Zhoushan port are used to complete the network training, and then, the trained network model is used to predict the cargo throughput of a port from May to December 2020, and the error is calculated by using the actual data. The port cargo throughput prediction algorithm based on the ant colony optimization proposed in [25], the port cargo throughput prediction algorithm based on SVM proposed in [26], and the proposed algorithm are used to predict the port cargo throughput, respectively.

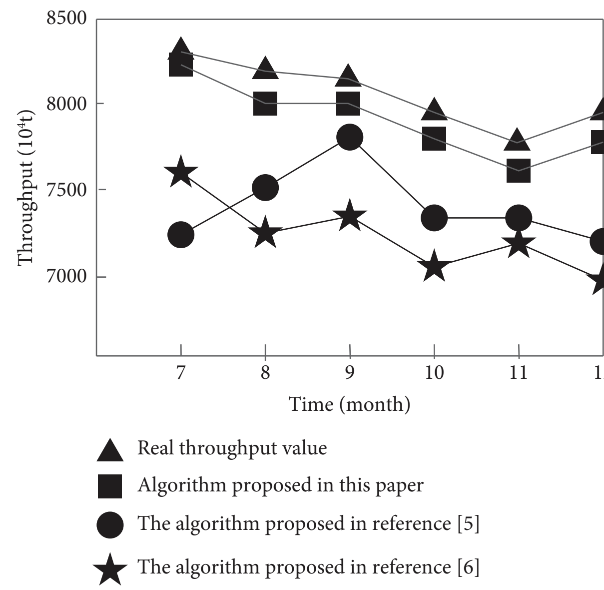

Figure 3: Predicted and actual values of different algorithms.

4.2.1. Prediction Error of Different Algorithms. The prediction results and corresponding prediction errors of the three algorithms are shown in Figures 3 and 4.

It can be seen from Figures 3 and 4 that compared with the reference algorithm, the prediction results of the port cargo throughput of the proposed algorithm are obviously closer to the actual value. At the same time, its prediction results fluctuate less, which proves that it has better stability.

4.2.2. Accuracy Test of Different Algorithms. The throughput prediction model is verified by residual test to realize the accurate prediction of the port cargo throughput. The

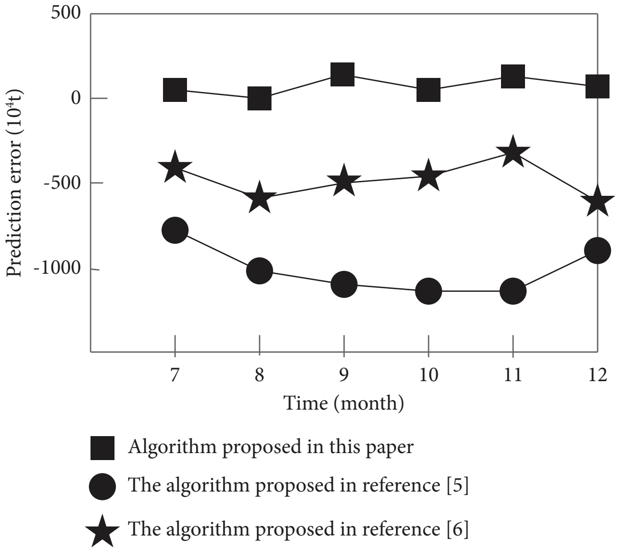

Figure 4: Prediction error of different algorithms.

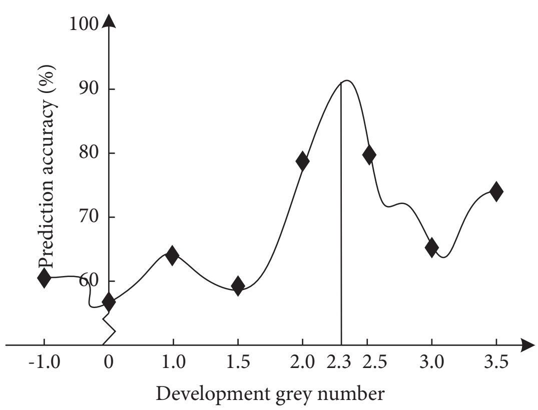

Figure 5: Development grey number change curve.

prediction effect of the cargo throughput prediction model depends on the parameter $-a$ (development grey number). According to the existing reference research, when $-a \leq 0.3$ 0, the model meets the medium and long-term throughput prediction demand. When $0.3 < -a \leq 0.5$, the model meets the demand of short-term throughput prediction. When $0.5 < -a \leq 0.8$, the model has large error in short-term throughput prediction. When $0.8 < -a \leq 1$, the accuracy of the model is poor and the residual needs to be corrected. When $-a > 1$, the prediction effect of the model is poor, so it is not recommended to apply the model.

According to the given experimental data, the optimal development grey number of the throughput prediction model is determined, and its change curve is shown in Figure 5.

As shown in Figure 5, when the development grey number is 1.8, the prediction accuracy of the model is the largest, so the best development grey number is 1.8.

According to the above description, in order to meet the prediction demand of the port cargo throughput, the development grey number range is determined as $[-0.5, +\infty]$, and the best development grey number needs to be selected according to the specific prediction demand.

Residual test refers to detecting the difference between the predicted value and the actual value of the model. The absolute residual sequence, relative parameter sequence, and average residual sequence are obtained by calculation, and the expression is as follows:

$$\begin{cases} \Delta(k) = \left[x(k) - x^{(1)}(k+1)\right], \\ \phi(k) = \left[\dfrac{\Delta(k)}{x(k)}\right]\%, \\ \overline{\phi}(k) = \dfrac{1}{n-1}\displaystyle\sum_{k=2}^{n}|\phi(k)|. \end{cases} \tag{11}$$

Based on the above experimental preparation data and the determined optimal development grey number, the throughput prediction simulation experiment is carried out to reflect the performance of the proposed method through the throughput prediction residual and accuracy. The specific experimental results and analysis process are as follows. The residual data of the cargo throughput obtained through experiments are shown in Table 3.

The division of accuracy standard is shown in Table 4.

The prediction performance of different neural networks shall be analyzed and evaluated in an all-round way by using the four evaluation indexes of the absolute percentage error maximum $\mathrm{MAX_{APE}}$, mean absolute error (MAE), average absolute percentage error (D_{MAPE}), and mean square root squared error (RMSE). Among them, the maximum absolute percentage error represents the percentage of the maximum error between the predicted value and the actual value to the actual value; the average absolute error represents the mean of the absolute value of the predicted error and reflects the accuracy; the average absolute percentage error is an indicator of the overall effectiveness of the forecasting method; the root-mean-square error reflects the dispersion of the predicted value and the actual value. The four evaluation indicators are as follows:

$$\begin{aligned} \mathrm{MAX_{APE}} &= 100\max_{i=1}^{n}\left(\left|\frac{d_f - d_i}{d_i}\right|\right), \\ P_{\mathrm{MAE}} &= \frac{1}{n}\sum_{i=1}^{n}\left|d_f - d_i\right|, \\ D_{\mathrm{MAPE}} &= \frac{100}{n}\sum_{i=1}^{n}\left|\frac{d_f - d_i}{d_i}\right|, \\ J_{\mathrm{RMSE}} &= \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(d_f - d_i\right)^2}, \end{aligned} \tag{12}$$

where d_f is the predicted value of the port cargo throughput and d_i is the actual value of the port cargo throughput.

From the evaluation results in Table 5, we can see that the prediction performance of the proposed algorithm is better than that of other two algorithms, and the performance is much better. Therefore, in the prediction of the port cargo

Table 3: Residual data of the cargo throughput.

Time	Actual value (10000 tons)	Predicted value (10000 tons)	Residual (10000 tons)	Relative residual (%)
2020–07	30.52	30.73	0.44	2.58
2020–08	35.81	32.24	−0.25	2.00
2020–09	37.36	39.21	0.74	2.07
2020–10	23.78	41.19	−0.97	2.71
2020–11	32.20	56.98	−0.36	1.04
2020–12	56.26	83.12	−0.49	1.80

Table 4: Division of accuracy standards.

Accuracy class	Describe	Numerical value
Level 1	Excellent	>95%
Level 2	Qualified	>80%
Level 3	Barely qualified	>70%
Level 4	Unqualified	≤70%

Table 5: Comparison of test indexes of different algorithms.

Evaluating indicator	Three algorithms		
	The algorithm proposed in [25]	The algorithm proposed in [26]	The algorithm proposed in this paper
MAX_{APE}	7.8	8.5	1.2
P_{MAE}	653.8	465.2	65.1
D_{MAPE}	7.1	5.6	0.9
J_{RMSE}	692.5	467.1	80.3

throughput with time characteristics, the proposed algorithm has better prediction performance and the prediction result is closer to the actual value. The experimental results show that the prediction precision of the proposed method accords with the grade 1 standard of grey system principle, which fully indicates that the proposed method has good prediction effect.

5. Conclusions and Outlook

Currently, the existing prediction algorithm of the port cargo throughput neglects the correction of the initial value of the cargo series data model, leading to a large error in the port cargo throughput prediction. So far, the port has developed to the fourth generation, whose development mode is the most efficient, namely, the supply chain mode serving the integration of trade, manufacturing industry, and logistics. Nowadays, an intelligent port aims to improve the efficiency of the port operation and management, which is also a test of port construction and management. The accurate prediction of the cargo throughput provides a basis for the planning, deployment, and reasonable allocation of tasks in advance, avoids the occurrence of a cargo backlog in the port, does not affect the delivery of goods and customer satisfaction, and fully improves the operating efficiency of the port, forming a virtuous circle. Therefore, accurate and reasonable forecast of the port cargo throughput is very important for port layout and even transformation and upgrading. As a result, we designed a prediction algorithm of the port cargo throughput based on the ES-Markov model. The ES-Markov model is constructed to modify the initial predicted value of the sample data. Based on the final results of the time-series arrangement and ES-Markov model, the port cargo throughput prediction algorithm is designed. The experimental results show that compared with the reference algorithm, the error of the prediction result of the port cargo throughput of the proposed algorithm is smaller and the prediction result is more stable, indicating that the application performance of the proposed algorithm is better. Besides, the experimental findings indicate that the prediction precision of the proposed method accords with the grade 1 standard of grey system principle, which fully indicates that the proposed method has good prediction effect.

Data Availability

No data were used to support the findings of the study.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

The study was supported by "Planning subject for the 13th five year plan of Educational Science in Guangdong Province, China (Grant no. 2020GXJK140)."

References

[1] M. Santos, E. Radicchi, and P. Zagnoli, "Port's role as a determinant of cruise destination socio-economic sustainability," *Sustainability*, vol. 11, no. 17, pp. 4542–4553, 2019.

[2] R. Lotfi, Y. Z. Mehrjerdi, and N. Mardani, "A multi-objective and multi-product advertising billboard location model with attraction factor mathematical modeling and solutions,"

International Journal of Applied Logistics, vol. 7, no. 1, pp. 64–86, 2017.

[3] C. Liu, D. Wu, Y. Li, and Y. Du, "Large-scale pavement roughness measurements with vehicle crowdsourced data using semi-supervised learning," *Transportation Research. Part C, Emerging Technologies*, vol. 125, Article ID 103048, 2021.

[4] J. Wang, H. Li, and X. Wang, "How the evolution of water transportation conditions and port throughput affected agricultural products logistics industry," *Journal of Coastal Research*, vol. 107, no. sp1, pp. 328–335, 2020.

[5] B. Bathaei, "Change is of the essence, regenerating of Brown fields (landscape revitalization of tehran's brick kilns)," in *Proceedings of the 2nd International Conference on Architecture, Structure and Civil Engineering (ICASCE'16)*, UK, London, March 2016.

[6] F. Ouyang, "Construction of integrated management model of port logistics supply chain based on big data," *Journal of Coastal Research*, vol. 93, no. sp1, pp. 1053–1065, 2019.

[7] J. Liu, "A grey theory-based economic prediction method of port and ocean engineering," *Journal of Coastal Research*, vol. 106, no. sp1, pp. 197–216, 2020.

[8] F. Meng, A. Pang, X. Dong et al., "H∞ optimal performance design of an unstable plant under bode integral constraint," *Complexity*, vol. 2018, Article ID 4942906, 10 pages, 2018.

[9] C. Zhao, F. Liao, X. Li, and Y. Du, "Macroscopic modeling and dynamic control of on-street cruising-for-parking of autonomous vehicles in a multi-region urban road network," *Transportation Research. Part C, Emerging Technologies*, vol. 128, Article ID 103176, 2021.

[10] Y. Du, B. Qin, C. Zhao, Y. Zhu, J. Cao, and Y. Ji, "A novel spatio-temporal synchronization method of roadside asynchronous MMW radar-camera for sensor fusion," *IEEE Transactions on Intelligent Transportation Systems*, pp. 1–12, 2021.

[11] M. Shafiei Nikabadi and S. B. Razaviyan, "Identification and ranking of effective indicators on the loyalty of the charities in Iranian charities using Fuzzy Delphi and Structural Interpretative Equation," *Quarterly Journal of Socio-Cultural Development Studies*, vol. 6, no. 3, pp. 59–79, 2018.

[12] C. Zong, H. Wang, and Z. Wan, "An improved 3D point cloud instance segmentation method for overhead catenary height detection," *Computers & Electrical Engineering*, vol. 98, Article ID 107685, 2022.

[13] S. Liu, J. Zhang, B. Niu, L. Liu, and X. He, "A novel hybrid multi-criteria group decision-making approach with intuitionistic fuzzy sets to design reverse supply chains for COVID-19 medical waste recycling channels," *Computers & Industrial Engineering*, vol. 169, Article ID 108228, 2022.

[14] B. Bathaei, "Achieving sustainable city by the concept of Persian garden," *Acta Technica Napocensis: Civil Engineering & Architecture*, vol. 61, no. 3, 2018.

[15] B. Bathaei and M. Abdel-Raheem, "Assessment of the relative importance of the main parameters used in the selection of the urban heat island mitigation strategies," in *Proceedings of the Construction Research Congress*, pp. 627–636, Arlington, Virginia, March 2022.

[16] M. Younesi Heravi, A. Yeganeh, and S. B. Razavian, "Using fuzzy approach in determining critical parameters for optimum safety functions in mega projects (case study: Iran's construction industry)," in *Frontiers in Nature-Inspired Industrial Optimization*, pp. 183–200, Springer, Singapore, 2022.

[17] Y. Li, P. Che, C. Liu, D. Wu, and Y. Du, "Cross-scene pavement distress detection by a novel transfer learning framework," *Computer-aided Civil and Infrastructure Engineering*, vol. 36, no. 11, pp. 1398–1415, 2021.

[18] L. Xu, X. Liu, D. Tong, Z. Liu, L. Yin, and W. Zheng, "Forecasting urban land use change based on cellular automata and the PLUS model," *Land (Basel)*, vol. 11, no. 5, p. 652, 2022.

[19] S. Lu, Y. Ban, X. Zhang et al., "Adaptive control of time delay teleoperation system with uncertain dynamics," *Front. Neurorobot.*vol. 16, Article ID 928863, 2022.

[20] C. A. Li, X. Q. Lu, Z. Q. Wu, and L. j. Zhang, "Throughput prediction of port based on back propagation neural network optimized by ant colony algorithm," *Acta Metrologica Sinica*, vol. 41, no. 11, pp. 88–93, 2020.

[21] X. Chen, D. Li, and L. H. Zhang, "Port throughput forecast of Jingzhou port based on improved SVM model," *Port & Waterway Engineering*, vol. 567, no. 03, pp. 48–52, 2020.

[22] C. Wang, D. Li, and Y. Zhang, "Application of dynamic improved grey model in airport throughput prediction," *Computer Simulation*, vol. 36, no. 12, pp. 74–77, 2019.

[23] S. Shankar, P. V. Ilavarasan, S. Punia, and S. P. Singh, "Forecasting container throughput with long short-term memory networks," *Industrial Management & Data Systems*, vol. 120, no. 3, pp. 425–441, 2019.

[24] M. Rocha de Paula, N. Boland, A. T. Ernst, A. Mendes, and M. Savelsbergh, "Throughput optimisation in a coal export system with multiple terminals and shared resources," *Computers & Industrial Engineering*, vol. 134, no. 10, pp. 37–51, 2019.

[25] S. Maldonado, R. G. Gonzalez-Ramirez, F. Quijada, and A. Ramirez-Nafarrate, "Analytics meets port logistics: a decision support system for container stacking operations," *Decision Support Systems*, vol. 121, no. 06, pp. 84–93, 2019.

[26] J. Yang and L. Guo, "Optimization of marine port logistics collection and distribution network: a perspective of supply chain management," *Journal of Coastal Research*, vol. 106, no. sp1, p. 473, 2020.

[27] R. Jin and L. Maibaum, "Mechanisms of DNA hybridization: transition path analysis of a simulation-informed Markov model," *The Journal of Chemical Physics*, vol. 150, no. 10, pp. 105103–111557, 2019.

[28] U. Ainuddin, M. Khurram, and S. M. R. Hasan, "Cloning the λ switch: digital and markov representations," *IEEE Transactions on Nano Bioscience*, vol. 18, no. 3, pp. 428–436, 2019.

[29] T. Niu, L. Zhang, B. Zhang, B. Yang, S. Wei, and P. Manfredi, "An improved prediction model combining inverse exponential smoothing and Markov chain," *Mathematical Problems in Engineering*, vol. 2020, no. 5, Article ID 6210616, 11 pages, 2020.

[30] S. Kadaei, S. M. Shayesteh Sadeghian, M. Majidi, Q. Asaee, and H. H. Mehr, "Hotel construction management considering sustainability architecture and environmental issues," *Shock and Vibration*, vol. 2021, Article ID 6363571, 13 pages, 2021.

[31] B. Bathaei, "Process analysis of environmental perception of persian garden based on psychological theory of environment," *Editura Universitar "Ion Mincu"*, vol. 124, 2016.

[32] S. Kadaei, *Human Presence in the Architectural Environment (From a Phenomenological Perspective)*, 138 pages, Bid Publishing, Tehran, 2020.

[33] G. Wu and Y. C. Hu, "Forecasting cargo throughput of main ports in circum-bohai bay region using grey model," *Journal of Management & Decision Sciences*, vol. 2, no. 1, pp. 8–14, 2019.

[34] A. N. Gutierrez, A. R. Carranza, and A. G. Carrasco, “Detecting nonlinear dynamics using BDS test and surrogate data in financial time series,” *Mathematics and Systems Science*, vol. 25, no. 2, pp. 46–53, 2019.
[35] S. Selvi and M. Chandrasekaran, “Framework to forecast environment changes by optimized predictive modelling based on rough set and Elman neural network,” *Soft Computing*, vol. 24, no. 14, pp. 10467–10480, 2020.
[36] X. Gong, L. Wang, Y. Mou et al., “Improved four-channel PBTDPA control strategy using force feedback bilateral teleoperation system,” *International Journal of Control, Automation and Systems*, vol. 20, no. 3, pp. 1002–1017, 2022.
[37] L. Yin, L. Wang, W. Huang et al., “Haze grading using the convolutional neural networks,” *Atmosphere*, vol. 13, no. 4, p. 522, 2022.
[38] H. Yang, X. Li, W. Qiang, Y. Zhao, W. Zhang, and C. Tang, “A network traffic forecasting method based on SA optimized ARIMA-BP neural network,” *Computer Networks*, vol. 193, no. 3, pp. 108102–108123, 2021.
[39] R. Lotfi, H. Nazarpour, A. Gharehbaghi, S. M. H. Sarkhosh, and A. Khanbaba, “Viable closed-loop supply chain network by considering robustness and risk as a circular economy,” *Environmental Science and Pollution Research International*, 2022.
[40] Z. Xie, X. Feng, and X. Chen, “Partial least trimmed squares regression,” *Chemometrics and Intelligent Laboratory Systems*, vol. 221, Article ID 104486, 2022.
[41] Z. Zhang, C. Luo, and Z. Zhao, “Application of probabilistic method in maximum tsunami height prediction considering stochastic seabed topography,” *Natural Hazards*, vol. 104, no. 3, pp. 2511–2530, Dordrecht, 2020.
[42] J. Mou, P. Duan, L. Gao, X. Liu, and J. Li, “An effective hybrid collaborative algorithm for energy-efficient distributed permutation flow-shop inverse scheduling,” *Future Generation Computer Systems*, vol. 128, pp. 521–537, 2022.
[43] C. Zong and Z. Wan, “Container ship cell guide accuracy check technology based on improved 3D point cloud instance segmentation,” *Brodogradnja*, vol. 73, no. 1, pp. 23–35, 2022.