A New Container Throughput Forecasting Paradigm under COVID-19

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Contributor: Anqiang Huang

COVID-19 has imposed tremendously complex impacts on the container throughput of ports, which poses big challenges for traditional forecasting methods. Combining this with change-point analysis and empirical mode decomposition (EMD), this uses the decomposition–ensemble methodology to build a throughput forecasting model. Firstly, EMD is used to decompose the sample data of port container throughput into multiple components. Secondly, fluctuation scale analysis is carried out to accurately capture the characteristics of the components. Subsequently, here tailor the forecasting model for every component based on the mode analysis. Finally, the forecasting results of all the components are combined into one aggregated output.

Keywords: container throughput forecasting ; EMD ; decomposition

1. Introduction

As an essential node for the realization of international trade, ports are not only the core infrastructure for building a global transportation system, but are also an important part of building an international supply chain [1]. The operation of the port transportation industry is a “barometer” of national macro-economy. The fluctuation of container throughput can directly reflect the prosperity and development of word trade. The sudden outbreak and spread of COVID-19 has had a great impact on the safe operation and management of China’s ports in the short term [2].

The World Health Organization (WHO) declared the outbreak of COVID-19 to be a public health emergency of international concern on 31 January 2020, and defined COVID-19 as a pandemic on 11 March 2020 [3]. In order to control the spread of the epidemic, governments around the world have taken different levels of preventive and control measures, which, while interrupting the spread of the virus, have also negatively impacted maritime trade. Measures such as restrictions on ship activity and work stoppages can lead to a decline in transportation and hinder the development of the world economy [4][5]. The scale and duration of the impact of COVID-19 will cause fluctuations and oscillations in port container throughput.

The time series of port container throughput is superimposed by linear or nonlinear data, and is usually affected by accidental events. The reasonable decision of port management for the influence of major events relies on the reliability and superiority of forecasting. The accurate forecasting of the container throughput is central to the planning of the government transportation departments at the micro and macro levels; it also plays an important role in the investment planning and stable operations of the port [6].

However, the container throughput data contains a variety of complex superimposed components. The traditional forecasting techniques cannot effectively capture the impact of major events on the forecast results, and it is difficult to obtain forecast results that can be used to guide practice. It is necessary to establish a port container throughput forecasting method with high extensibility and that is suitable for the common scenarios of major events. Firstly, the EMD is used to decompose the original observed data into a finite number of Intrinsic Mode Functions (IMFs). Then, the data characteristics of different IMFs are analyzed by means of a smoothness test, model fluctuation scale analysis, structural breakpoint test, etc. Subsequently, the components are predicted by using ARIMA or SVR according to the data characteristics and the results of significant event determination. Finally, the final forecasting results are obtained by ADD. The results show that the proposed model can effectively capture the degree of impact of the new crown epidemic on container throughput, and the forecasting accuracy is higher than that of EMD-SVR, SVR, and ARIMA.

2. Forecasting Model

Predictive techniques can generally be divided into three main categories: econometric models, artificial intelligence models (AI), and hybrid algorithms.

In the field of container throughput forecasting, some traditional economic models have been frequently used, such as the autoregressive integrated moving average (ARIMA) model [7], the seasonal autoregressive integrated moving average (SARIMA) model [8][9], the exponential smoothing model [10], the error correction model (ECM) [11], the auto-regressive conditional heteroscedasticity (ARCH) model [12], the multiple regression model [13], the vector autoregressive (VAR) model [14], and the grey forecasting model [15][16]. However, these econometric models are unable to capture the nonlinear part of the original data. These econometric models have poor forecasting performance, particularly with regard to some nonlinear time series data.

Therefore, artificial intelligence (AI) models are used to describe nonlinear characteristics in the time series of container throughput. These AI models include the grey neural network [17][18], the discrete particle swarm optimization [19][20], the back-propagation neural network (BPNN) model [21], fuzzy neural networks [22], etc. In recent years, artificial intelligence technology has been constantly innovated and developed. Yu et al. [23] mentioned that, in the application of artificial intelligence technology, SVR (support vector regression algorithm), LSSVR (least squares support vector regression algorithm), and ANN (artificial neural network algorithm) are considered as the main applied artificial intelligence forecasting models. These three models can predict linear stationary and nonlinear stationary data with high precision, which are superior to econometric models in terms of forecasting performance (e.g., ARIMA). However, artificial intelligence models also have drawbacks such as the potential local optimum, the sensitivity of parameter selection [24], and complex computational operations.

Substantial hybrid approaches have been developed for better forecasting performance. Huang et al. [25] combined projection pursuit regression (PPR) with a genetic programming (GP) algorithm and proposed a hybrid method to forecast the container throughput of Qingdao Port. Based on the hybrid theory, Yu et al. [26] proposed a “decomposition and ensemble” or “divide and conquer” approach.

3. Decomposition Methods in Forecasting

By decomposition and ensemble, the proposed method can effectively improve the forecasting accuracy [23]. Xie et al. [27] proposed a hybrid forecasting method based on a combination of least squares supported vector regression (LSSVR) and a preprocessing method that includes SARIMA, seasonal decomposition (SD), and classical decomposition (CD). Yu et al. [28] proposed a sparse representation (SR) as a decomposition tool for the integrated forecasting of complex time series, greatly improving the forecasting accuracy of crude oil prices. Jianwei et al. [29] used variational mode decomposition (VMD) to decompose and forecast oil prices. Yu et al. [30] applied EMD-based neural network ensemble learning paradigms to forecast the world crude oil spot price. EMD is a common data decomposition tool proposed by Huang et al. [31]. This method decomposed nonlinear and non-stationary time series into several Intrinsic Mode Functions (IMFs). EMD has been widely used in many fields. EMD also provides a multi-scale framework to analyze the impact of extreme events, which has been successfully applied to crude oil price analysis, among others [32][33]. In order to grasp the impact of the epidemic event on each model feature of the port, the iterative cumulative sum of squares (ISCC) algorithm and Chow test mentioned by Inclán and Tiao [34] can be combined to conduct the structural change-point test for each feature model. The EMD decomposition tool is considered as a powerful data decomposition tool with a wide range of applications.

Most of the current forecasting studies employing various decomposition algorithms directly use components of the original data for forecasting without applying event analysis.

4. Forecasting Considering COVID-19

Many scholars analyze the epidemic to improve the forecasting accuracy and study the impact of the epidemic on the fluctuation of the forecasting. Wu et al. [35] proposed a novel oil price, production, and consumption forecasting methodology. They input the text features of oil news headlines in the context of COVID-19 into some common forecasting models, such as BPNN, SVM, etc. Wu et al. [36] forecast crude oil prices by using convolutional neural network (CNN) and variational mode decomposition (VMD) to extract and process text features in online news. Weng et al. [37] proposed a modeling framework, the genetic algorithm regularization online extreme learning machine with forgetting factor (GA-RFOS-ELM), to estimate the effects of news during COVID-19 on the volatility of crude oil futures. Stifanic et al. [38]

integrated the stationary wavelet transform (SWT) and bidirectional long short-term memory (BDLSTM) networks to predict commodity and stock price movement during COVID-19. Koyuncu et al. [39] forecast the container throughput index with the time series. They examined the relationship between the short-term estimate of the container throughput index and COVID-19.

A majority of current studies forecast crude oil prices, commodity prices, stock prices, container throughput index, etc., considering COVID-19.

Different from the existing studies, this is the first study to propose a hybrid decomposition–ensemble forecasting model integrating event analysis into the container throughput forecasting tasks, which provides a powerful tool for forecasting tasks considering the impact of major events, e.g., COVID-19.

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