Comprehensive Forecasting Model for Port Container Throughput Based on Hybrid Deep Neural Networks

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Abstract. Port container throughput holds considerable importance for port construction planning and operational decision-making management. The problem of container throughput forecasting essentially entails modeling a nonlinear dynamic system driven by multiple variables. To improve the predictive precision of container throughput and to process various types of complex, nonlinear data, the variational mode decomposition (VMD) algorithm is employed to perform feature decomposition on the container throughput series. A hybrid deep neural network based on CNN-GRU is then constructed to decipher the complex mapping relationships between the influencing factors and feature sequences, culminating in the development of a comprehensive VMD-CNN-GRU port container throughput forecasting model. Empirical analysis is conducted on the container throughput series from the Guangzhou port to test the predictive effectiveness of the proposed integrated model. Comparative experimental analysis with various models indicates that the proposed integrated model yields the best predictive results, confirming its effectiveness and accuracy. This model provides support for port container throughput forecasting tasks.

Keywords: container throughput, sequence decomposition, neural networks, Guangzhou port

1 Introduction

In the port and shipping industry, the port container throughput reflects a port's transport capacity and productivity. Accurate forecasting of container throughput provides scientific decision-making support for port administrators and is of great significance in port planning, construction, and operational management. Container throughput forecasting constitutes a time series prediction issue pertinent to port operation management. Fundamentally, it involves understanding and modeling a dynamic, nonlinear system driven by multiple variables. Forecasting models are required to reflect the complex relationships between various influencing factors and throughput, while also possessing the capability to process and analyze large volumes of historical data, in order to capture and utilize the inherent patterns within this data.

In existing research, forecasting methods for container throughput can be divided into two categories: single models and combined models. Single forecasting models are

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typically divided further into mathematical statistics models, machine learning models, and deep learning models. Mathematical statistics models include methods like exponential smoothing [1], seasonal autoregressive integrated moving average model [2], and grey forecasting model [3]. These models usually assume that time series data exhibit linear properties, which can be ineffective in identifying and adapting to the complexity of container throughput data characterized by non-linearity and dynamic volatility, leading to suboptimal forecasting performance. Machine learning methods mainly include backpropagation neural network models [4] and support vector machine models [5]. Studies have shown that machine learning models outperform traditional mathematical statistical models [6]. Deep learning models have been less applied in container throughput forecasting studies. For instance, the long short-term memory (LSTM) network has been used, by Shankar et al. [7] who established an LSTM model to forecast container throughput at the Singapore port, showing that the LSTM model's forecasting performance surpasses that of traditional models. As research has progressed, scholars have found that combined models perform better than single models. In the realm of combined forecasting models, the original complex series is typically decomposed into linear and non-linear residual subsequences, which are then predicted separately [8]. Mo et al. [9] decomposed the original container throughput series into linear and non-linear residual sequences, using the autoregressive integrated moving average model to predict the linear subsequence and an ensemble of traditional non-linear models for the non-linear residual subsequence, with the cumulative results significantly enhancing the overall predictive performance of the model. Kulshrestha et al. [10] employed a decomposition and ensemble framework to develop a multivariate container throughput forecasting model based on NA-MEMD-BiLSTM, validating its effectiveness with a case study at the Port of Singapore.

It is found that existing combined modeling methods for port container throughput often consider the throughput series as a superposition of linear and non-linear sequences. However, the throughput of containers at different ports does not always follow a monotonic increasing trend. It is more rational to abstract the container throughput series as a superposition of non-linear sequences with different fluctuation frequencies. LSTM is a commonly utilized model for time series prediction, yet compared to it, the gated recurrent unit (GRU) network model boasts a simpler structure with fewer parameters, faster model training, and superior predictive performance [11-12]. Therefore, for the prediction of container throughput, the GRU network model emerges as a more suitable candidate. However, the feature extraction capability of a single GRU is limited when handling complex data, whereas the robust data feature extraction function of convolutional neural networks (CNN) [13] can effectively address this issue. Thus, integrating CNN with GRU to leverage the strengths of both technologies for container throughput prediction is highly meaningful.

In light of the aforementioned objectives, this paper proposes a novel data-driven approach leveraging deep learning techniques to achieve accurate predictions of container throughput. Specifically, the primary contributions of this paper are as follows: the application of the variational modal decomposition (VMD) algorithm to decompose the container throughput time series, followed by the training of an optimal combined CNN-GRU model on each decomposed sequence for prediction, and finally, the ensemble of the individual predictive results of each sequence to obtain the overall forecast outcome. Moreover, by comparing the predictive performance of various deep neural network models, the VMD-CNN-GRU model's forecasting capabilities have been validated to outperform other models.

2 Approach

2.1 VMD-Based Throughput Sequence Decomposition

Container throughput is influenced by a multitude of factors and its time series exhibits multiple nonlinear characteristics, presenting highly complex and irregular fluctuations. Directly learning from the original series, neural network models are prone to underfitting or overfitting, and thus may fail to accurately decipher the original sequence. The container throughput time series encompasses components such as long-term trends, seasonal fluctuations, and irregular variations, necessitating series decomposition and individual model analysis to enhance predictive accuracy. The variational mode decomposition [14] (VMD) method can address this issue effectively. VMD is a technique for decomposing non-stationary and non-linear signals, based on the assumption that a signal is composed of a superposition of modes, each of which can be approximately considered as a harmonic signal with a finite bandwidth [15]. The principle of the algorithm is to decompose the original complex sequence into several modes with finite bandwidth, where each mode is essentially an oscillatory waveform centered around a specific frequency, ensuring that the sum of all modes equals the original signal. By using VMD algorithm, a port container throughput series (yt) can be decomposed into a series of intrinsic mode functions (IMFs) and a residual sequence (rt), as in equation (1):

$$y_t = \sum_{i=1}^{n} \mathrm{IMF}_i + r_t \tag{1}$$

2.2 GRU-Based Throughput Forecasting Model

When establishing a container throughput forecasting model, it is imperative not only that the model accurately identifies nonlinear fluctuation characteristics within long historical data sequences but also that it can parse the complex mapping relationships between influencing factors and throughput. With this objective, the gated recurrent unit network (GRU) [16] based on recurrent neural networks (RNN) [17] serves as an excellent starting point. The GRU network is a variant of the RNN, with a network structure that features short-term memory capabilities and powerful computing abilities, making it particularly suitable for processing time-series data. GRU were initially designed to improve upon LSTM networks, incorporating a gating mechanism to control the way information is updated. The GRU have only two gate structures: the update gate and the reset gate, which simplifies the model structure and reduces the number of parameters, resulting in faster model training. The GRU unit structure is shown in

Figure 1. The update gate determines how the hidden state is updated, while the reset gate decides how much of the past information should be retained when computing the current candidate hidden state. These two gating mechanisms work together, allowing the GRU network to selectively forget and remember information, thereby providing superior performance when processing sequential data.

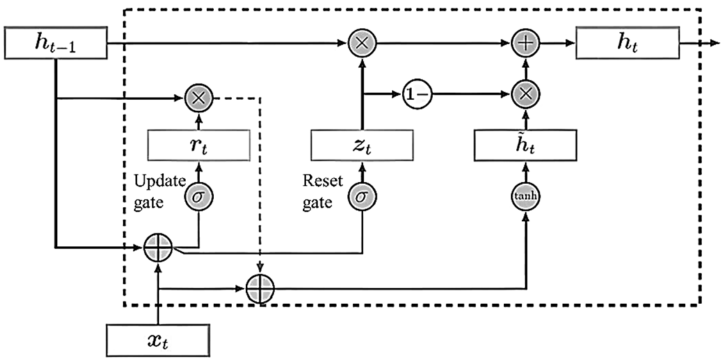

Fig. 1. The GRU unit structure

2.3 Comprehensive Forecasting Model VMD-CNN-GRU

The comprehensive forecasting model for port container throughput based on VMD-CNN-GRU constructed in this paper is shown in Figure 2, and the overall steps of this model are as follows:

Step 1: Data collection and organization, where quantifiable data on factors affecting container throughput and the throughput series itself are collected, with preprocessing applied to the gathered data.

Step 2: The VMD decomposition algorithm is used to decompose the original container throughput series into three characteristic sequences, including long-term trend modes, seasonal fluctuation modes, and residuals.

Step 3: Using the data of influencing factors and historical time series as inputs, an optimal hybrid deep neural network CNN-GRU model is separately trained for each decomposed sequence. After decomposing the complex series of container throughput into three different characteristic sequences, modeling is performed on each decomposed sequence individually. To further enhance the model's predictive performance and enable it to handle a variety of complex data, this paper establishes a hybrid deep neural network forecasting model that combines CNN with GRU networks (CNN-GRU). This is primarily because the model's feature extraction capability significantly impacts the prediction results. The convolutional neural network can automatically detect and extract local features from the input sequence data through its convolutional layers, which greatly enhances the model's feature extraction ability and thus improves the prediction outcomes. In the CNN-GRU hybrid deep neural network, the convolutional, pooling, and flattening layers of the CNN are inserted before the GRU network layers. Through this section, convolution operations are performed on the input data for abstract feature extraction, retaining important features and excluding noise to prevent overfitting. Then the processed stable information is fed as a whole into the GRU network for training and prediction, with the final results output through a fully connected layer.

Step 4: Parallel predictions are made for each decomposed sequence using the optimal hybrid deep neural network CNN-GRU model, obtaining predicted sequences.

Step 5: The three prediction sequences obtained by each parallel prediction are added together to obtain the final prediction result of container throughput.

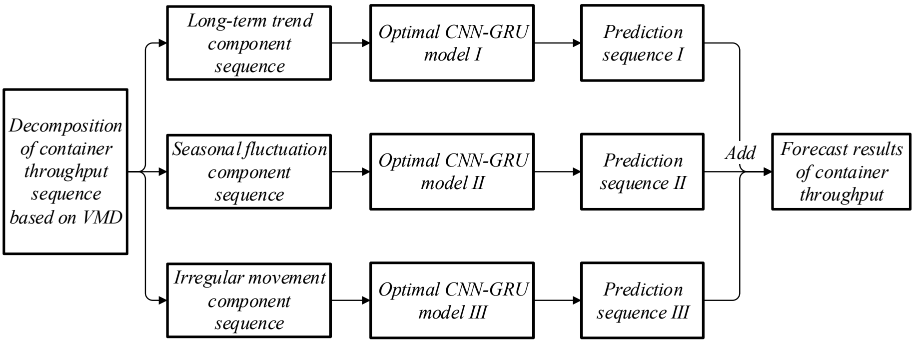

Fig. 2. The comprehensive forecasting model based on VMD-CNN-GRU

3 Empirical Analysis

3.1 Data Source

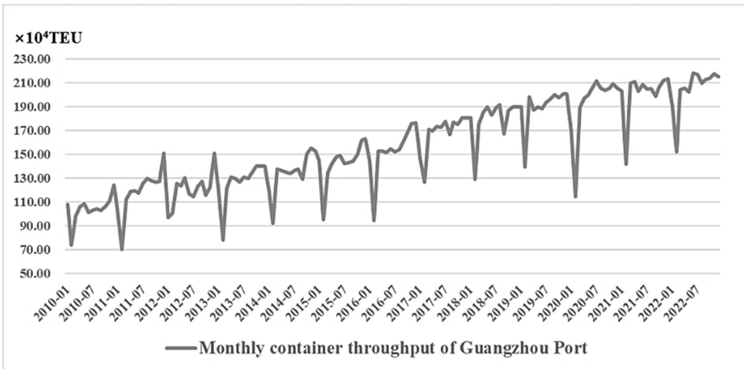

Fig. 3. Monthly container throughput of Guangzhou Port

This paper conducts an empirical analysis using the container throughput series from Guangzhou port as an example. The experimental data sample consists of monthly container throughput data of Guangzhou port from 2010 to 2022. Figure 3 shows the data from the official website of China's Ministry of Transport. In addition, data on influencing factors were collected, including regional GDP, total retail sales of consumer goods, total import and export volume, waterway freight volume, and road freight volume, sourced from the Guangzhou Municipal Bureau of Statistics and other agencies. The data are divided into training, validation, and test sets. Specifically, the training set includes data from January 2010 to December 2020, the validation set from January 2021 to December 2021, and the test set from January 2022 to December 2022. The training set is used for model training; the validation set is used to verify the model's training effectiveness. If the training results are unsatisfactory, the model parameters are adjusted, and the model is retrained. After multiple adjustments, the optimal model is obtained, which is finally tested on the test set that has never been involved in the training process.

3.2 Evaluation Criteria for Model Performance

This paper uses three error metrics to calculate the final prediction error of the comprehensive model, to assess the predictive performance of the comprehensive model. These metrics are the mean absolute error (MAE), mean absolute percentage error (MAPE), and root mean square error (RMSE) [10]. Their specific calculations are as in equation (2) ~ (4):

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|\hat{y}_i - y_i\right| \tag{2}$$

$$\mathrm{MAPE} = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{\hat{y}_i - y_i}{y_i}\right| \tag{3}$$

$$\mathrm{RMSE} = \left(\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2\right)^{1/2} \tag{4}$$

Where n represents the total number of samples in the dataset; $\hat{y}_i$ denotes the predicted value; y_i is the actual value. The smaller the values of the MAE, MAPE, and RMSE metrics, the better the predictive performance and the higher the accuracy of the model.

3.3 Experimental Results and Comparative Analysis

The simulation experiments were conducted in the Windows system using MATLAB2022b, and the hardware was equipped with a graphics processing unit (GPU). The overall predictive performance of the VMD-CNN-GRU integrated forecasting model and multiple comparison models on the container throughput of Guangzhou port is shown in Figure 4. The forecasting results are very good, with the evaluation metrics MAE, MAPE, and RMSE being 3.4088, 1.6865%, and 3.9990, respectively.

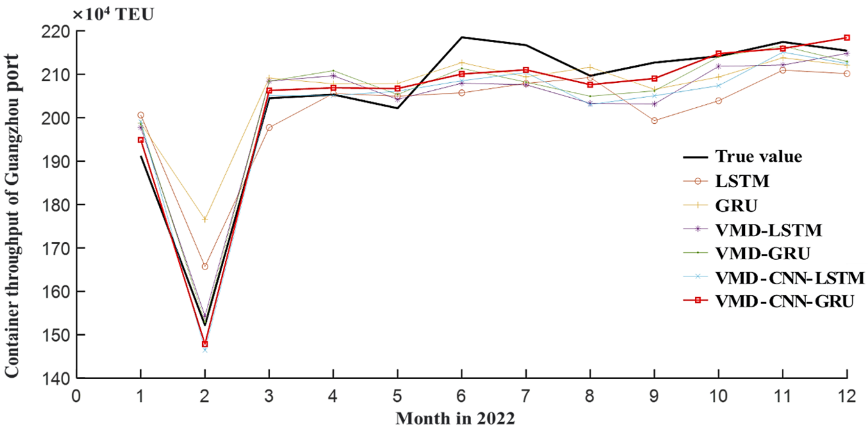

Fig. 4. Comparison of prediction results of multiple models

To verify the effectiveness and accuracy of the model, this paper carried out comparative experiments between the comprehensive forecasting model constructed in this paper and the VMD-CNN-LSTM model, VMD-GRU model, VMD-LSTM model, GRU model, and LSTM model. The specific results of the comparative experiments among the six models are shown in Table 1.

Table 1. Comparison of evaluation metrics of the six models.

Model	MAE	MAPE（%）	RMSE
LSTM	7.5083	3.7675	8.7551
GRU	6.4787	3.4641	8.5943
VMD-LSTM	5.2281	2.5151	6.0959
VMD-GRU	4.2597	2.0534	5.0416
VMD-CNN-LSTM	5.0908	2.5110	5.8747
VMD-CNN-GRU	**3.4088**	**1.6865**	**3.9990**

Comparative experimental results indicate that, under the same conditions, the predictive performance of models incorporating GRU, both single and combined, is superior to those with LSTM, demonstrating that the performance of GRU is superior to that of LSTM. In the comparison between the VMD-GRU model and the GRU model, the former shows significant improvements in the three evaluation metrics—MAE, MAPE, and RMSE—by 34.25%, 40.72%, and 41.34%, respectively. This indicates that the

VMD decomposition strategy significantly enhances the predictive performance of the single GRU network model. In the comparison between the VMD-CNN-GRU model and both the VMD-GRU model and the GRU model, the former shows improvements of 19.98%, 17.87%, and 20.68% over the VMD-GRU model, and 47.38%, 51.31%, and 53.47% over the GRU model in MAE, MAPE, and RMSE, respectively. The results demonstrate that the incorporation of the CNN network further enhances the model's predictive performance, and the combination of CNN and GRU is significantly better than LSTM.

In the predictive simulation results for the container throughput of Guangzhou port, the VMD-CNN-GRU model achieved the lowest values in the three error metrics—MAE, MAPE, and RMSE—proving that the VMD-CNN-GRU model provides the most accurate forecasting results and the best model performance among the six comparison models.

4 Conclusion

Accurately forecasting port container throughput is essential for the planning, construction, and operational management of ports. To enhance the predictive accuracy of container throughput and handle various types of complex, nonlinear data, this paper introduces the VMD algorithm for feature decomposition of the container throughput series. A hybrid deep neural network based on CNN-GRU is constructed to unravel the intricate mapping relationships between influencing factors and feature sequences. Consequently, a comprehensive VMD-CNN-GRU based forecasting model for port container throughput is proposed and validated using the container throughput series from Guangzhou port. Comparative experiments with multiple models demonstrate that the model proposed in this paper possesses the highest predictive accuracy, thereby verifying its reliability and accuracy. The comprehensive forecasting model provides a reference for forecasting port container throughput, and its applicability could be extended to a wider range of port throughput forecasting tasks, supporting port production management and operational decision-making.

However, the comprehensive prediction model based on hybrid deep neural networks in this paper has some shortcomings in terms of insufficient stability and long operation time. In future research, more efficient data analysis techniques can be incorporated, the network architecture of predictive models can be innovated, and the generalization ability of models can be improved to process different types of complex data and adapt to the rapidly changing development environment.

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