Research on Time Series Forecast of Container Throughput Based on Selective Deep-Ensemble Model

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Abstract. Accurate forecast of container throughput is an important basis for reasonably planning port construction, making port operation plan and adjusting port development direction. Aiming at the complex nonlinear characteristics of port container throughput, a hybrid model based on selective deep-ensemble for container throughput forecasting (HMSD) is presented in this paper. Firstly, this model decomposes the original container throughput time series into several intrinsic mode functions and a residual by empirical mode decomposition (EMD). Considering highly nonlinear characteristics of each intrinsic mode function, the proposed model constructs three deep neural networks, namely, long short term memory (LSTM), gated recurrent unit (GRU) and convolutional neural network (CNN), as base learners to predict intrinsic mode functions. Then, this model establishes selective deep-ensemble forecasting model by improved group method of data handling (GMDH) on intrinsic mode functions and obtains their ensemble forecasting results. Furthermore, this model uses an autoregressive integrated moving average model to predict the linear residual. Finally, the forecasting result of the total container throughput is obtained by integrating the forecasting results of all intrinsic mode functions and the residual. The empirical analysis of container throughput data of Xiamen port and Shanghai port in China shows that the HMSD model has better forecasting effect than other models.

1. Introduction

Container as a standardized loading mode eliminates the differences in the appearance of the goods transported, and plays an important role in shortening the transportation time of goods and reducing the cost of trading. It is very suitable for the maritime transportation of bulk stock, and has become the most important form of cargo transportation in China's foreign trade [1-2]. The Ministry of Transport of the People’s Republic of China has shown that China container throughput in November 2020 reached 241.4 million twenty-foot equivalent units (TEU), a year-on-year growth of 0.8% against the global container throughput decline trend. With the upsurge of container transport development, the booming construction of ports resulted in a number of problems, such as overcapacity and declined throughput capacity utilization [3]. Container port infrastructure construction is an irreversible investment. Once excessive construction and overcapacity occurs, the port will suffer huge economic losses [4]. Therefore, the accurate forecast of container throughput is of great significance to the adjustment of port development direction, the formulation of port operation plan and the planning of port layout.

2. The basic idea of hybrid model based on selective deep-ensemble

In this paper, time series \( \{y_t \}_{t=1,2,\ldots,T_0} \) presents the original container throughput. The proposed HMSD model mainly includes the following three stages: (1) Decompose the time series of original
container throughput by EMD. The original time series \( \{y_t\} \) is decomposed into several intrinsic mode functions \( \{imf^k_{\ell}|k = 1, 2, \ldots, n\} \) and the residual \( r^n_t \) by EMD. (2) Predict intrinsic mode functions and the residual from the decomposition respectively. Firstly, we need construct base learners on each intrinsic mode function, and get their predict results. The intrinsic mode function \( imf^k_{\ell} \) is the dependent variable, the lag terms of \( imf^k_{\ell} \) in \( q \) order \( \{imf^k_{\ell}^{\ell-q}|q = 1, 2, \ldots, m, m < t - 1\} \) forms the independent variable. Thus, we train three candidate base learners, LSTM, GRU and CNN, to predict each intrinsic mode function, and obtain the prediction results \( \{imf^k_{\ell}^{p}|p = 1, 2, 3\} \). For example, when we predict the \( k \)-th intrinsic mode function \( imf^k_{\ell} \), we need to transform the intrinsic function and its corresponding prediction result \( \hat{imf}^k_{\ell} \) into the data set \( D \) in matrix form stored, as shown in Table 1. The first \( l \) rows of the data set in this table are taken as the testing set \( Test \), and the last \( T_0 - l \) rows are taken as the training set \( Train \), and \( Train \) is divided into two subsets with three base learners as units: model learning set \( A \) and model selection set \( B \). Further, the improved GMDH model is run to select the candidate base learners in self-organizing and obtain the optimal complexity model, which is used to predict each intrinsic function, and the result is written as \( \hat{imf}^k_{\ell} \). Finally, train the ARIMA model to predict the residual. The ARIMA model is run to predict the residual \( r^n_t \), and the result is written as \( \hat{r}^n_t \). (3) Calculate the final container throughput forecast results. The final prediction results of the original container throughput \( \hat{y}_t = \sum_{k=1}^{n} \hat{imf}^k_{\ell} + \hat{r}^n_t \) can be obtained by adding the prediction results of all intrinsic mode functions and the residual.

| Table 1. Transformation matrix of intrinsic mode functions |
|---|---|---|---|
| Test set | \( imf^T_{k0} \) | \( \ldots \) | \( imf^T_{k0-l+1} \) |
| \( \ldots \) | \( \ldots \) | \( \ldots \) | \( \ldots \) |
| \( \ldots \) | \( \ldots \) | \( \ldots \) | \( \ldots \) |
| \( \ldots \) | \( \ldots \) | \( \ldots \) | \( \ldots \) |
| Train set | \( imf^T_{k0-l} \) | \( \ldots \) | \( imf^T_{k0-l+1,1} \) |
| \( \ldots \) | \( \ldots \) | \( \ldots \) | \( \ldots \) |
| \( \ldots \) | \( \ldots \) | \( \ldots \) | \( \ldots \) |
| \( \ldots \) | \( \ldots \) | \( \ldots \) | \( \ldots \) |

3. Empirical analysis
In this paper, the HMSD model is used to forecast the container throughput of Shanghai Port and Xiamen Port. A number of comparative experiments are designed, including the comparison with the single model and the hybrid model based on EMD decomposition, and the hybrid model based on simple decomposition, so as to comprehensively verify the prediction effect of the HMSD model.

3.1. Experimental data
The data for modeling are from the official website of Ministry of Transport of the People’s Republic of China and “Yearbook Ports of China” [5-6]. This study utilizes the monthly container throughput data of Shanghai and Xiamen ports from January 2001 to December 2019 for the experiment, and takes the data from January 2001 to December 2017 as the training set and data from January 2018 to December 2019 as the test set. Figure 1 shows the original container throughput time series of the two ports. The container throughput data of these ports have strong cyclicity and volatilities.
3.2 Evaluation criteria
Four different evaluation criteria are selected in this paper, including root mean square error (RMSE), absolute mean percentage error (MAPE), mean absolute scaled error (MASE), and predictive directionality index $D_{stat}$ [7].

\[
RMSE = \sqrt{\frac{\sum_{t=1}^{m} (\hat{y}_t - y_t)^2}{m}} \tag{1}
\]

\[
MASE = \frac{m-1}{m} \sum_{t=1}^{m} \frac{|y_t - \hat{y}_t|}{\sum_{t=2}^{m} |y_t - y_{t-1}|} \tag{2}
\]

\[
MAPE = \frac{\sum_{t=1}^{m} |\hat{y}_t - y_t|}{m} \tag{3}
\]

\[
D_{stat} = \frac{1}{m} \sum_{t=2}^{m} a_t, a_t = \begin{cases} 1, & (y_t - y_{t-1})(\hat{y}_t - \hat{y}_{t-1}) > 0 \\ 0, & \text{other} \end{cases} \tag{4}
\]

where, $y_t$ is the actual value at moment $t$, $\hat{y}_t$ is the corresponding prediction value, and $m$ is the sample size of the test set. The smaller the value of RMSE, MASE and MAPE are, the better effect model has. The larger the value of $D_{stat}$ is, the better effect model has.

3.3 Decomposition results of EMD
The decomposition results of original container throughput by EMD at Shanghai Port and Xiamen Port are shown in Figure 2. The horizontal axis represents the number of months since January 2001, 1 represents January 2001, 50 represents February 2005, and so on. The vertical axis represents the container throughput, which is in $10^4$ TEU. As can be seen from the figure, the original container throughput time series of Shanghai Port and Xiamen Port are decomposed into four intrinsic mode functions $i_{m}f_1, i_{m}f_2, i_{m}f_3, i_{m}f_4$ and a residual $r$. From $i_{m}f_1$ to $i_{m}f_4$, the cyclicity of the intrinsic mode function becomes longer, and the frequency becomes lower. The residual is series with long cyclical and low frequency, almost linear trend. The simple decomposition method decomposes the original time series into two parts: linear subseries and nonlinear subseries. The linear and nonlinear subseries can be regarded as the residual and intrinsic mode functions decomposed by EMD respectively. The intrinsic mode functions are a further division of the nonlinear subseries and have a more concise fluctuation trend.
3.4 The prediction results and comparative experiments of intrinsic mode functions

3.4.1 The prediction results of a single deep neural network
In this study, three deep neural networks, LSTM, GRU and CNN, are constructed to predict each intrinsic mode function of Shanghai Port and Xiamen Port, and the prediction results are compared to find out the best model on each intrinsic mode function. Table 2 presents the RMSE, MAPE, MASE and Dstat values of the three models on the test set, as well as their average rank. The bold values in the table represent the optimal prediction results of the model under the current criteria. The rank in the table is obtained by calculating the average value of the four evaluation criteria for each model on the corresponding intrinsic mode function. The higher the rank is, the better the prediction effect of the model is.

The following conclusions can be drawn from Table 2: (1) In the prediction of intrinsic mode functions in Shanghai Port, the rank of LSTM model is the highest on \( \text{imf}_5 \), \( \text{imf}_6 \) and \( \text{imf}_7 \), indicating that the prediction effect of LSTM on these three intrinsic mode functions is the best. On the \( \text{imf}_8 \), the model with the best prediction effect is GRU, which only has the best performance on \( \text{RMSE} \) and \( \text{Dstat} \), but has the highest rank. (2) In the prediction of intrinsic mode functions in Xiamen Port, the LSTM has the best prediction effect on \( \text{imf}_5 \), \( \text{imf}_6 \) and \( \text{imf}_7 \), which all ranks first in the three criteria. On the \( \text{imf}_8 \), the model with the best prediction performance is GRU, which has the best performance on all criteria.

Further analysis shows that from \( \text{imf}_3 \) to \( \text{imf}_4 \), the prediction errors of all models decrease gradually. At Shanghai port, the RMSE of the best model on \( \text{imf}_4 \) is lower than 0.3, and the RMSE of the best model on \( \text{imf}_3 \) is also significantly lower than \( \text{imf}_4 \). At Xiamen port, the RMSE of the best model on \( \text{imf}_3 \) and \( \text{imf}_4 \) have been reduced to less than 0.3 and 0.06 respectively. By analyzing the experiment results, two conclusions are drawn as follows: (1) Applying deep neural network to container throughput prediction can obtain better results. (2) Different fluctuation frequency of intrinsic mode functions leads to different prediction effect. The prediction of high frequency time series is more difficult than low frequency time series.
Table 2. Forecasting results of single deep neural network models on intrinsic mode functions

| Series | Model | Shanghai Port | Xiamen Port |
|--------|-------|---------------|-------------|
|        |       | **RMSE** | **MAE** | **MAPE** | **Dstat** | **Rank** | **RMSE** | **MAE** | **MAPE** | **Dstat** | **Rank** |
| `imf_1` | LSTM  | 8.3408 | 0.2461 | 1.1005 | 0.8696 | 2.3865 | **0.2795** | **0.6345** | 0.9565 | 1.3 |
|        | GRU   | 8.6603 | 0.2991 | 1.5771 | 0.6957 | **2.3127** | 0.3106 | 1.0973 | 0.6522 | 2.5 |
|        | CNN   | 10.1667 | 0.3767 | 1.8927 | 0.7391 | 2.5377 | 0.2865 | 0.7728 | 0.7826 | 2.3 |
| `imf_2` | LSTM  | 4.6141 | 0.4382 | 0.2195 | 0.9130 | 0.9485 | 0.3251 | 0.3951 | 0.8261 | 2 |
|        | GRU   | 4.0423 | 0.3620 | 0.2672 | 0.8696 | **0.9294** | **0.3137** | **0.3822** | **0.8969** | 1 |
|        | CNN   | 5.6108 | 0.5563 | 0.3557 | **0.9130** | 1.7814 | 0.6341 | 0.7229 | 0.7391 | 3 |
| `imf_3` | LSTM  | 0.9921 | 0.2181 | **0.0669** | 0.9565 | 1.7711 | 0.1683 | 0.1674 | **1.0000** | 1.4 |
|        | GRU   | **0.9144** | 0.2355 | 0.0776 | **1.0000** | 0.2502 | 0.2368 | **0.1302** | **1.0000** | 2.1 |
|        | CNN   | 0.9447 | **0.2179** | 0.1094 | 0.9565 | 0.2333 | 0.2114 | 0.1951 | 0.9565 | 2.5 |
| `imf_4` | LSTM  | 0.1716 | 0.2098 | 0.0699 | **0.0600** | **0.0238** | **0.1290** | 0.0281 | **1.0000** | 1.5 |
|        | GRU   | 0.2239 | 0.2646 | **0.0398** | **1.0000** | 0.0549 | 0.2785 | 0.1087 | **1.0000** | 2.8 |
|        | CNN   | 0.2916 | 0.3637 | 0.1194 | **1.0000** | 0.0246 | 0.1294 | 0.2159 | 0.9565 | 2.5 |

3.4.2 Prediction results of selective deep-ensemble model based on GMDH

In this section, we construct the selective deep-ensemble model based on GMDH to predict all intrinsic mode functions of Shanghai Port and Xiamen Port, and compare the prediction results with the single model. The experiment results are shown in Table 3. By comparing Table 2 and Table 3, it can be found that: (1) The criteria value of selective deep-ensemble model based on GMDH are all better than the single model, which indicates that the improved GMDH model can still run effectively with fewer initial models, and improve the prediction effect of the single model. (2) In `imf_3` and `imf_4` of the two ports, the ensemble model doesn’t significantly improve the prediction effect compared with the single model. This is because the fluctuation patterns of these low-frequency series are relatively simple, and the single model can achieve better prediction effect. Therefore, in practical applications, high frequency series decomposed by EMD can be predicted by ensemble model, while low frequency series can be predicted by single model, which can not only improve the overall prediction accuracy of the model, but also save modeling time and computational resources.

Table 3. GMDH selective deep ensemble forecasting results of intrinsic mode functions

| Port    | Intrinsic mode function | Optimal complexity model | `imf_1` | `imf_2` | `imf_3` | `imf_4` |
|---------|-------------------------|--------------------------|--------|---------|---------|---------|
| Shanghai Port | `imf_1`  | LSTM, GRU               | LSTM, GRU        | LSTM, GRU | LSTM, GRU | LSTM, GRU |
|          | `imf_2`  | 5.0007                  | 2.8536            | 0.4671   | 0.0521   |         |
|          | `imf_3`  | 0.2109                  | 0.2733            | 0.0190   | 0.0037   |         |
|          | `imf_4`  | 1.0297                  | 0.3088            | 0.0386   | 0.0119   |         |
|          | Dstat    | 0.9130                  | 1.0000            | 1.0000   | 1.0000   |         |
| Xiamen Port | `imf_1`  | LSTM, CNN               | LSTM, GRU, CNN  | LSTM, GRU | LSTM, GRU | LSTM, GRU |
|          | `imf_2`  | 1.6856                  | 0.6096            | 0.1301   | 0.0172   |         |
|          | `imf_3`  | 0.1891                  | 0.0579            | 0.0593   | 0.0160   |         |
|          | `imf_4`  | 0.7243                  | 0.3569            | 0.0826   | 0.0179   |         |
|          | Dstat    | 1.0000                  | 1.0000            | 1.0000   | 1.0000   |         |

3.5 Comparative experiments of hybrid models

In order to verify the prediction effect of the hybrid model under the EMD decomposition condition, this paper compares HMSD with three hybrid models based on the single model, EMD-LSTM-ARIMA, EMD-GRU-ARIMA and EMD-CNN-ARIMA, and a hybrid model EMD-AVERAGE-ARIMA based on weighted average ensemble. Table 4 presents the prediction results of each model, and the bold values in the table indicate that the corresponding model has the best performance under the current criteria. As can be seen from the table: (1) In Shanghai Port, HMSD, EMD-LSTM-ARIMA and EMD-
AVERAGE-ARIMA models have the best performance on $D_{stat}$ from the perspective of forecasting direction, while the other two models have the same results on this criterion. From the perspective of prediction error, HMSD has the best performance in all three error criteria. The performance of EMD-LSTM-ARIMA and EMD-AVERAGE-ARIMA is slightly worse than HMSD, and EMD-LSTM-ARIMA has better performance on $MASE$ and $MAPE$. Compared with EMD-GRU-ARIMA, EMD-CNN-ARIMA model is slightly worse on $RMSE$, but better on $MASE$ and $MAPE$. (2) In Xiamen Port, the model with the best performance is HMSD, which has the best performance in $RMSE$, $MASE$ and $MAPE$. The prediction performance of the other four models is similar, but EMD-GRU-ARIMA has obvious advantages in the direction of prediction, and its $D_{stat}$ value is the best among all the models. Therefore, HMSD is the best prediction model in both ports, which shows that selective deep-ensemble model based on GMDH can use self-organizing modeling technology to make up for the information lack of the single model and information redundancy of ensemble model which ensembles all base learners, and can effectively improve forecasting precision of the container throughput.

| Port      | Prediction model     | RMSE    | MASE    | MAPE    | $D_{stat}$ |
|-----------|----------------------|---------|---------|---------|------------|
| Shanghai  | EMD-LSTM-ARIMA       | 9.1646  | 0.2946  | 0.0186  | 0.7826     |
|           | EMD-GRU-ARIMA        | 11.7398 | 0.4192  | 0.0261  | 0.6957     |
|           | EMD-CNN-ARIMA        | 11.1978 | 0.4356  | 0.0272  | 0.6957     |
|           | EMD-AVERAGE-ARIMA    | 9.0463  | 0.3258  | 0.0204  | 0.7826     |
|           | HMSD                 | 8.6159  | 0.2759  | 0.0172  | 0.7826     |
| Xiamen    | EMD-LSTM-ARIMA       | 2.7268  | 0.4763  | 0.0246  | 0.5263     |
|           | EMD-GRU-ARIMA        | 2.5699  | 0.4418  | 0.0221  | 0.6316     |
|           | EMD-CNN-ARIMA        | 2.5223  | 0.4530  | 0.0229  | 0.5789     |
|           | EMD-AVERAGE-ARIMA    | 2.3904  | 0.4019  | 0.0213  | 0.5789     |
|           | HMSD                 | 2.3231  | 0.4003  | 0.0206  | 0.5263     |

### 3.6 Comparative experiments of hybrid models based on EMD decomposition and simple decomposition

In order to study the influence of different decomposition methods on the prediction performance of the hybrid model, we respectively construct the hybrid model based on EMD decomposition and simple decomposition to forecast the container throughput of Shanghai Port and Xiamen Port. The prediction results are shown in Table 5. The bold values in this table indicate that the hybrid model has the best performance on the current criteria under the corresponding decomposition method. It can be seen from the table that in the prediction results of Shanghai Port, the HMSD model performs better than SARIMA-GMDH in the four evaluation criteria. Compared on the three error criteria, the prediction performance of HMSD model is significantly better than SARIMA-GMDH which is superior on directivity criterion $D_{stat}$.

Further analysis of the experiment results can draw the following conclusions: (1) Compared with the simple decomposition method, the EMD decomposition method is more detailed in the decomposition of time series, but the hybrid model based on EMD is not necessarily superior to the hybrid model based on simple decomposition in all criteria. (2) The detailed decomposition of complex series by EMD can help improve the prediction effect of the model, while for simple linear series, the simple decomposition can achieve better prediction results. (3) The prediction effect of HMSD is better than SARIMA-GMDH in both ports, which indicates that under the condition of EMD decomposition, the prediction effect of the model can be effectively improved by using selective deep-ensemble model of GMDH.
| Port      | Prediction model | RMSE  | MASE  | MAPE  | Dstat  |
|----------|------------------|-------|-------|-------|--------|
| Shanghai Port | HMSD             | 8.6159| 0.2759| 0.0172| 0.7826 |
|          | SARIMA-GMDH      | 12.3652| 0.4394| 0.0275| 0.6087 |
| Xiamen Port | HMSD             | 2.3231| 0.4003| 0.0206| 0.5263 |
|          | SARIMA-GMDH      | 4.2519| 0.5795| 0.0386| 0.5826 |

### 4. Conclusion

In summary, the HMSD model can firstly be used to improve the accuracy of container throughput forecasting, assist the daily operation and management activities of the port, such as port capacity allocation and pricing strategy, and guide future planning and development. Secondly, in the realistic container throughput prediction task, the high frequency series decomposed by EMD are predicted by selective deep-ensemble model based on GMDH, and the low frequency series are predicted by a single model, which can not only improve the overall prediction accuracy of the model, but also save modeling time and computational resources. Finally, the HMSD model constructed in this paper has strong adaptability. Based on the same principle and prediction method, the model can also be extended to the related prediction research in the fields of energy, economic and power. In addition, considering reference function with adjustable, GMDH neural network in model building can also set the reference function to other forms, such as second order nonlinear function or third-order nonlinear function with square item, a more complex reference function may lead to better prediction effect, which is worthy of further discussion in future research issues.

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