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CONTAINER THROUGHPUT FORECASTING FOR INTERNATIONAL PORTS IN TAIWAN

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Key words: container throughput forecasting, univariate forecasting models, forecasting accuracy comparison.

ABSTRACT

This paper compares different univariate forecasting methods and provides a more accurate short-term forecasting model for container throughput to create a reference for relevant authorities. Six different univariate methods, including the classical decomposition model, the trigonometric regression model, the regression model with seasonal dummy variables, the grey forecasting model, the hybrid grey forecasting model, and the seasonal autoregressive integrated moving average (SARIMA) model, were used. We found that the SARIMA model is a reliable forecasting method for forecasting container throughput with seasonal variations. This study's findings can help to predict the near-future demand for container throughput at international ports.

I. INTRODUCTION

Containerization plays a vital role in the rapid growth of international trade, particularly for island countries like Taiwan. The global competition associated with shipping routes significantly influences port operations, construction, and facility upgrades. Growth in container throughput is one of the most important determinants of massive and irreversible investments in port infrastructure development. Building port infrastructure usually entails a considerable loss of time in port or limited access to port facilities during construction. The inability to make accurate predictions regarding future port throughput may result in devastating financial losses related to port construction or facility enhancement projects. Therefore, accurate forecasting of future throughput is crucial for the construction, upgrade, and daily operational management of ports (Peng and Chu, 2009).

While long-term forecasts for port operations are the most mainstream forecasting method, short-term forecasts are also important. In monitoring changes in seasonal patterns and business cycles, short-term forecasts often yield better results than long-term forecasts (Franses and Van Kijk, 2005). Short-term forecasts, which cover a period of one or two years, are typically used for daily port operations, including the allocation and arrangement of workers and machines and the acquisition of additional equipment and material. Since these forecasts are conducted for shorter periods, fewer unexpected factors may arise. In practice, the results of short-term forecasts are more accurate than those of long-term forecasts. Furthermore, unlike manufacturing industries, a container terminal's capacity cannot be increased immediately in response to seasonal variations in demand by adopting strategies such as keeping inventory, outsourcing, and overtime work. Therefore, short-term forecasts are essential for the scheduling and control of a container port system as well as decision-making and planning.

In this study, we adopted univariate forecasting methods to predict future port throughput based on past throughput values. We analyzed historical data to identify a pattern and assumed that the recognized historical pattern would continue into the future. To forecast seasonal variations, we utilized monthly data for six models: the classical decomposition model, the trigonometric regression model, the regression model with seasonal dummy variables, the grey forecasting model, the hybrid grey forecasting model, and the seasonal autoregressive integrated moving average (SARIMA) model. This study seeks to compare different univariate forecasting methods and provide a more accurate short-term forecasting model for container throughput to create a reference for authorities.

The remainder of our paper is organized as follows: Section 2 provides the literature review. Section 3 discusses the research methodology. A comparison of the results obtained from all methods is presented in Section 4. Finally, Section 5 provides the concluding remarks.

II. LITERATURE REVIEW

Most previous studies regarding the prediction of container throughput have been based mainly on long-term forecasting. Regression analysis is a popular forecasting method, which involves identifying and measuring causal relationships among

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variables (Seabrooke et al., 2003; Gosasang et al., 2018). As mentioned in Coto-Millán et al. (2003), it is necessary to identify the determinants of marine exports and imports in regression models. Considering the estimation errors caused by uncertainty in forecasting, some researchers have highlighted the need to implement forecasting adjustments by employing alternate techniques. For instance, multivariate time-series models were used to forecast maritime steel traffic flow in the Port of Antwerp (De Gooijer and Klein, 1989).

A commonly used short-term forecasting method is extrapolation. Several other methods have been employed in previous literature. Babcock et al. (1999) applied a time-series model to forecast quarterly railroad grain carloadings. By adopting a time-series model, Babcock et al. (2002) forecasted inland waterway grain traffic. Chou et al. (2003) used a SARIMA model to forecast Kaohsiung Port's container volume. Fung (2002) and Hui et al. (2004) employed the error correction model to forecast Hong Kong's throughput. In 2004, Lam et al. proposed a neural network model to predict Hong Kong Port's cargo throughput, while Zhang and Kline (2007) utilized a neural network approach to forecast a quarterly time series. Using an extensive dataset of 756 quarterly time series from the M3 competition, Makridakis and Hibon (2000) conducted a comprehensive analysis of the effectiveness of data preprocessing and modeling approaches. Farhan and Ong (2018) utilized the SARIMA model to forecast container throughput at several major international container ports and found that the model was able to produce reliable throughput forecasts.

Huang et al. (2003) applied the grey theory to predict transportation demand in Taiwan. Veldman and Bückmann (2003) employed a logit model to quantify routing choices and derived a demand function to forecast port traffic at the port of Rotterdam. Combining traditional regression analysis and fuzzy set theory, Liang and Chou (2003) proposed a new fuzzy regression model to predict the import/export cargo volume for Taiwan's ports. Chou (2004) utilized a new method, graded multiple integrals representation, in a fuzzy calculation to predict the total import/export container volume in Taiwan's ports. Xiao et al. (2014) proposed a transfer-forecasting model, guided by a discrete particle swarm algorithm. They demonstrated the proposed model's effectiveness by using data regarding two important ports in China, the Shanghai and Ningbo Ports, for their empirical analysis.

Some studies compared the different forecasting methods that utilize time-series data. Chou (2004) employed fuzzy time series to predict export container volume and found that forecasts obtained using fuzzy time series were more accurate than those obtained using seasonal time series. Peng and Chu (2009) compared the results from six different seasonal forecasting models that utilized the container import volume data of three international ports in Taiwan. They suggested that the classical decomposition model is a reliable method for short-term forecasting. Huang and Kuo (2012) applied correlation analysis to determine the variables influencing container throughput in Taiwan. They adopted the grey forecasting model to predict future values of influential variables and utilized an artificial neural network to forecast container throughput in Taiwan. Recently, Chan et al. (2019) employed different time-series forecasting methods, including machine-learning-based methods such as support vector regression. In this study, we employed six time-series forecasting methods to forecast a port's container throughput and subsequently, compared the performances of these methods.

Some studies, however, focused on other factors rather than container volume. For example, Chu and Zhang (2003) compared the accuracy of various linear and nonlinear models for forecasting aggregate retail sales, while Taylor et al. (2006) compared univariate methods for forecasting short-term electricity demand. Pacchin et al. (2019) presented a comparison of different short-term water-demand forecasting models. Ramyar and Kianfar (2019) utilized neural networks to forecast crude oil prices and compared the results with those obtained using vector autoregressive models.

From previous literature, we found that the regression model is the most widely adopted method. It was also quite evident that most studies had focused on long-term forecasting. There is limited research that compared the performance of different forecasting methods in conjunction with conducting short-term forecasting. Thus, to fill this research gap, this study aimed to identify a practical yet highly accurate forecasting model.

III. METHODOLOGY

1. Classical decomposition model

In the classical decomposition model, time series are divided into four separate components: trend, cyclical, seasonal, and irregular components. The model is based on intuition rather than theory. There are two types of classical decomposition models: multiplicative and additive models. In this study, we adopted the multiplicative approach and expressed the time series as

$$Y_t = TR_t \times SN_t \times CL_t \times IR_t, \tag{1}$$

where Y_t is the observed value of the time series in time period t,
TR_t is the trend component in time period t,
SN_t is the seasonal component in time period t,
CL_t is the cyclical component in time period t, and
IR_t is the irregular component in time period t.

Since we utilized monthly data, we first calculated the 12-period moving average and denoted it as MA_k for period k. Next, the centered moving average at time k was calculated as $CMA_k = \frac{1}{2}\left(MA_k + MA_{k+1}\right)$. Since the trend and cyclical components were incorporated in the centralized moving average series, i.e., $CMA_k = TR_t \times CL_t$, in Equation (1), we calculated the product of the seasonal and irregular components of the time series as follows: $SI_t = SN_t \times IR_t = \frac{Y_t}{CMA_t}$. To remove the irregular component from SI_t, we estimated the average of the observations in month t for three successive years to obtain the seasonal variation component for month t, expressed as $SN_t = \frac{1}{3}\left(SI_t + SI_{t+12} + SI_{t+24}\right)$. Dividing Y_t by the seasonal index SN_t, we generated a de-seasonalized series ($\frac{Y_t}{SN_t}$), which was a better series for estimating the trend component TR_t. Next, the deseasonalized observations were used to estimate TR_t by further assuming a linear trend model as follows:

$$TR_t' = \alpha + \beta t + \varepsilon_t \tag{2}$$

Applying the least squares method to Equation (2) to obtain the point estimates for α and β, expressed as a and b, we obtained the following estimate for the trend component:

$$\hat{TR}'_t = a + bt \tag{3}$$

2. Trigonometric regression model

The trigonometric regression model can be used to forecast time series that exhibit seasonal variations. To allow for increasing seasonal variation, we utilized a general specification, suggested by Bowerman and O'Connell (1993), as follows:

$$\begin{aligned} Y_t = {} & \beta_0 + \beta_1 t + \beta_2 \sin\left[\frac{2\pi t}{L}\right] + \beta_3 t \cos\left[\frac{2\pi t}{L}\right] \\ & + \beta_4 \cos\left[\frac{2\pi t}{L}\right] + \beta_5 t \cos\left[\frac{2\pi t}{L}\right] \\ & + \beta_6 \sin\left[\frac{4\pi t}{L}\right] + \beta_7 t \sin\left[\frac{4\pi t}{L}\right] + \beta_8 \cos\left[\frac{4\pi t}{L}\right] \\ & + \beta_9 t \cos\left[\frac{4\pi t}{L}\right] + \varepsilon_t, \end{aligned} \tag{4}$$

where L denotes the number of periods within a year in the data. For example, if monthly data is considered, then L will be 12. A unique feature of the model is that it assumes a linear trend but contains terms that allow for a more complicated, increasing seasonal pattern.

3. Regression model with seasonal dummy variables

An alternate specification of the regression model is to use seasonal dummy variables to analyze seasonal variations. First, we assumed that time series can be separated into three components, as shown in the following equation:

$$Y_t = TR_t + SN_t + \varepsilon_t,$$

where TR_t is the trend component, SN_t is the seasonal variation component, and ε_t denotes the random component. Since the monthly data approach was used, we further assumed that seasonal variations could be captured by a set of dummy variables with one for each month, except the month treated as the norm, as follows:

$$SN_t = \sum_{i=1}^{11} \beta_{si} X_{si,t}, \tag{5}$$

where $X_{si,t} = \begin{cases} 1 & \text{if period t is month } i, i = 1,2,3,...,11, \\ 0 & \text{otherwise.} \end{cases}$

Finally, assuming a linear trend and substituting Equation (5) as per the above definition of the time series, we generated the following regression model:

$$\begin{aligned} Y_t = {} & \beta_0 + \beta_1 t + \beta_{s1} X_{s1,t} + \beta_{s2} X_{s2,t} \\ & + ... + \beta_{s11} X_{s11,t} + \varepsilon_t \end{aligned}. \tag{6}$$

Applying the least squares method to Equation (6), we expressed the forecasted value of the time series as

$$\begin{aligned} \hat{Y}_t = {} & b_0 + b_1 t + b_{s1} X_{s1,t} + b_{s2} X_{s2,t} \\ & + ... + b_{s11} X_{s11,t} \end{aligned}. \tag{7}$$

4. Grey forecasting model

The grey forecasting model (GM) is the core of the grey theory developed by Deng (1989). It is particularly suitable for forecasting in areas where incomplete information or uncertain behaviors are common problems. The grey theory comprises three basic operations: (1) accumulated generation, (2) inverse accumulated generation, and (3) grey modeling. A main characteristic and merit of the grey model is that it requires less data to generate forecasts. Grey forecasting models are characterized by the order of the differential equations associated with the model and the number of variables included. For instance, GM (1, 1) typically denotes a first-order and single-variable grey model. We briefly describe the steps used to generate forecasts for GM (1, 1) as follows.

Consider the initial sequence for a time series,

$$\begin{aligned} x^{(0)} & = \left(x^{(0)}(1), x^{(0)}(2), x^{(0)}(3), ..., x^{(0)}(n)\right) \\ & = \left(x^{(0)}(k); k = 1,2,3,...,n\right) \end{aligned}, \tag{8}$$

where $x^{(0)}(k)$ refers to the time series in period k. The next sequence $x^{(1)}$ was generated from the accumulated generating operation (AGO) of $x^{(0)}$. Specifically,

$$\begin{aligned} x^{(1)} & = \left(\sum_{k=1}^{1} x^{(0)}(k), \sum_{k=1}^{2} x^{(0)}(k), ..., \sum_{k=1}^{n} x^{(0)}(k)\right) \\ & = \left(x^{(1)}(1), x^{(1)}(2), x^{(1)}(3), ..., x^{(1)}(n)\right) \end{aligned}. \tag{9}$$

Next, we computed the class ratio $\sigma(k)$ as follows:

$$\sigma^{(1)}(k)=\frac{x^{(1)}(k-1)}{x^{(1)}(k)},\quad k\geq 2, \tag{10}$$

which tested whether the sequence was acceptable for constructing the model. If the original sequence $x^{(0)}(k)$ was non-negative and $\sigma^{(1)}(k)\in(0,1)$, then $x^{(1)}(k)$ would represent a grey index pattern in the AGO.

After completing the above test, we specified a first-order differential equation for GM (1, 1) as follows:

$$\frac{dx^{(1)}}{dk}+ax^{(1)}=b \tag{11}$$

where a and b denoted the coefficients to be determined. By definition,

$$\frac{dx^{(1)}}{dk}=\lim_{\Delta k\to 0}\frac{x^{(1)}(k+\Delta k)-x^{(1)}(k)}{\Delta k}.$$

As an approximation, we set $\triangle k=1$. Subsequently,

$$\frac{dx^{(1)}}{dk}=x^{(1)}(k)-x^{(1)}(k-1)=x^{(0)}(k). \tag{12}$$

Applying the mean value generating operation to $x^{(1)}$, we obtained

$$Z^{(1)}(k)=0.5x^{(1)}(k)+0.5x^{(1)}(k-1). \tag{13}$$

From Equations (12) and (13), we obtained the grey differential equation for GM (1, 1) as

$$x^{(0)}(k)+az^{(1)}(k)=b\quad k=2,3,4,\ldots,n. \tag{14}$$

Next, we applied the ordinary least squares method to Equation (14) to estimate the coefficients of a and b. After obtaining the estimated coefficients, $\hat{a}$ and $\hat{b}$, we substituted $\hat{a}$ and $\hat{b}$ in the following equation:

$$\hat{x}^{(1)}(k+1)=\left(x^{(0)}(1)-\frac{\hat{b}}{\hat{a}}\right)e^{-\hat{a}k}+\frac{\hat{b}}{\hat{a}}\quad\text{and}\quad \hat{x}^{(1)}(1)=x^{(0)}(1) \tag{15}$$

The predicted grey value of the time series could easily be calculated using the inverse accumulated generating operation (IAGO) to convert to $x^{(0)}(k)$ as follows:

$$\hat{x}^{(0)}(k+1)=\hat{x}^{(1)}(k+1)-\hat{x}^{(1)}(k) \tag{16}$$

5. Hybrid grey forecasting model

Tzeng et al. (2001) showed that the grey forecast of GM (1, 1) will always generate increasing or decreasing trends and hence, the grey model is insufficient to forecast time series with seasonality. They suggested a hybrid grey model by combining GM (1, 1) with the ratio-to-moving-average deseasonalization method. In this paper, we propose a hybrid grey model obtained by combining the grey model with the classical decomposition model. We also extend our analysis by varying the size of the initial sequence in the grey forecast and searching for the sequence with the lowest prediction errors. The calculation process is described as follows.

Step 1 We removed seasonal factors from the original time series. This step is identical to the classical decomposition model discussed in Section 3.1.

Step 2 We constructed a grey forecast model as discussed in Section 3.4 by setting K=4 for the initial sequence and calculating the prediction errors. Next, we increased the size of K to 5 and repeated the same calculations. We repeated the process until K=12. Finally, we identified which value of K provided the lowest prediction errors.

6. SARIMA

The well-known ARIMA model, suggested by Box and Jenkins (1976), is widely used to analyze stationary time-series data. In this technique, the time-series data is required to be stationary. By extending the ARIMA model to incorporate seasonal factors, we obtained the SARIMA model. The SARIMA model is denoted as *SARIMA(p, d, q)(P, D, Q)s*, where p refers to the order of autocorrelation, d is the number differencing required to make the series stationary, and q is the order of the moving average. P, D, and Q refer to the counterparts of p, d, and q, respectively, in a seasonal model. The model can be expressed as follows:

$$\varphi_p(B)\Phi_p(B^s)\nabla^d\nabla_s^D Z_t=\theta_q(B)\Theta_Q(B^s)\varepsilon_t, \tag{17}$$

where

Z_t is the stationary data point at time t,
s refers to the seasonality,
B is the backshift operator $B(Z_t)=Z_{t-1}$ with $B^m(Z_t)=Z_{t-m}$,
$\nabla_s^D=\left(1-B^s\right)^D$ is the seasonal differencing operator,
$\nabla^d=\left(1-B\right)$ is the non-seasonal operator,
$\psi_p(B)$ denotes the non-seasonal autoregressive operator of order p, defined as

$$(1-\psi_1 B-\psi_2 B^2-\cdots-\psi_p B^p),$$

$\theta_q(B)$ is the non-seasonal moving average operator of order

Table 1. Container throughput at Keelung Port

Unit: TEUs

Year	Month	TEU	Year	Month	TEU
2013	1	113,548	2016	1	94,321
2013	2	73,865	2016	2	66,249
2013	3	115,607	2016	3	97,222
2013	4	108,000	2016	4	97,904
2013	5	115,458	2016	5	99,906
2013	6	117,794	2016	6	97,896
2013	7	119,445	2016	7	92,076
2013	8	117,279	2016	8	94,319
2013	9	114,673	2016	9	81,009
2013	10	119,768	2016	10	93,671
2013	11	117,972	2016	11	95,500
2013	12	122,767	2016	12	101,054
2014	1	119,801	2017	1	83,740
2014	2	86,482	2017	2	76,935
2014	3	122,079	2017	3	99,461
2014	4	116,826	2017	4	95,803
2014	5	122,043	2017	5	100,014
2014	6	125,033	2017	6	98,313
2014	7	124,092	2017	7	95,665
2014	8	119,413	2017	8	98,846
2014	9	112,589	2017	9	98,301
2014	10	117,117	2017	10	95,011
2014	11	118,856	2017	11	104,848
2014	12	118,993	2017	12	104,457
2015	1	114,459			
2015	2	82,796			
2015	3	99,444			
2015	4	99,129			
2015	5	106,852			
2015	6	96,232			
2015	7	100,639			
2015	8	97,093			
2015	9	91,188			
2015	10	97,903			
2015	11	93,397			
2015	12	99,634			

Source: National Statistics, Republic of China (Taiwan)

q, defined as

$$(1-\theta_1 B-\theta_2 B^2-\cdots-\theta_q B^q),$$

$\Phi_P(B^s)$ and $\Theta_Q(B^s)$ are the seasonal operators of finite orders P and Q, respectively, and, ε_t is the white noise, which is assumed to be independently and identically distributed as random variables with zero mean and variance of σ^2.

The unknown parameters in Equation (17) can be estimated by inspecting the behavior of the auto-covariance function (ACF) and partial autocorrelation function (PACF) (Box et al., 1994). In practice, choosing the best model among several statistical models is an important issue. The most commonly used

Table 2. Container throughput at Taichung Port

Unit: TEUs

Year	Month	TEU	Year	Month	TEU
2013	1	106,179	2016	1	103,153
2013	2	78,260	2016	2	75,187
2013	3	119,348	2016	3	106,100
2013	4	101,833	2016	4	108,681
2013	5	113,020	2016	5	104,978
2013	6	105,437	2016	6	104,617
2013	7	105,280	2016	7	110,109
2013	8	106,054	2016	8	106,785
2013	9	100,397	2016	9	97,831
2013	10	103,017	2016	10	120,161
2013	11	106,518	2016	11	114,020
2013	12	108,119	2016	12	121,381
2014	1	99,068	2017	1	112,304
2014	2	90,465	2017	2	99,783
2014	3	108,582	2017	3	120,898
2014	4	106,947	2017	4	118,855
2014	5	108,023	2017	5	122,133
2014	6	113,256	2017	6	118,145
2014	7	112,780	2017	7	116,973
2014	8	118,747	2017	8	122,202
2014	9	97,847	2017	9	112,542
2014	10	103,799	2017	10	117,756
2014	11	113,161	2017	11	122,835
2014	12	108,467	2017	12	134,419
2015	1	116,493			
2015	2	86,110			
2015	3	109,988			
2015	4	108,316			
2015	5	108,727			
2015	6	103,545			
2015	7	101,171			
2015	8	99,091			
2015	9	89,261			
2015	10	101,780			
2015	11	96,565			
2015	12	98,532			

Source: National Statistics, Republic of China (Taiwan)

criteria are the Akaike information criterion (AIC) and the Schwarz Bayesian information criterion (SBC). These criteria assign penalties to a model as the number of parameters increases. Thus, adding a new or lag variable will decrease the square of the error sum but increase the penalty term. The best model can be determined by identifying the model that provides the smallest criterion value.

IV. DATA AND RESULTS

In this section, we first describe the data used in this study and then present the results from all six forecasting models. Next, we evaluate the results based on the three criteria mentioned and compare the forecasting accuracy of the models.

Table 3. Container throughput at Kaohsiung Port

Unit: TEUs

Year	Month	TEU	Year	Month	TEU
2013	1	711,870	2016	1	710,595
2013	2	574,688	2016	2	612,377
2013	3	729,435	2016	3	751,292
2013	4	708,313	2016	4	756,644
2013	5	733,526	2016	5	762,793
2013	6	676,979	2016	6	753,824
2013	7	732,032	2016	7	743,319
2013	8	701,995	2016	8	758,387
2013	9	701,045	2016	9	682,945
2013	10	737,304	2016	10	791,212
2013	11	711,537	2016	11	796,803
2013	12	758,857	2016	12	801,154
2014	1	744,243	2017	1	771,067
2014	2	640,931	2017	2	679,891
2014	3	742,419	2017	3	818,258
2014	4	756,752	2017	4	736,589
2014	5	753,472	2017	5	750,163
2014	6	765,373	2017	6	709,266
2014	7	748,933	2017	7	675,020
2014	8	751,974	2017	8	738,044
2014	9	741,978	2017	9	704,586
2014	10	791,309	2017	10	709,712
2014	11	772,124	2017	11	733,140
2014	12	782,162	2017	12	768,306
2015	1	725,993			
2015	2	615,423			
2015	3	765,254			
2015	4	744,745			
2015	5	754,419			
2015	6	718,580			
2015	7	713,890			
2015	8	719,812			
2015	9	705,663			
2015	10	713,407			
2015	11	708,722			
2015	12	734,222			

Source: National Statistics, Republic of China (Taiwan)

1. Time-series data on container throughput volumes in Taiwan

We collected monthly data regarding container throughput volumes for three major ports in Taiwan for the period from January 2013 to December 2017. We split the data into two datasets: an in-sample dataset for estimation and an out-of-sample dataset for prediction. The in-sample data covered the period from January 2013 to December 2016, while the out-of-sample data covered the period January–December 2017. The data regarding the container throughput volumes at the Keelung, Taichung, and Kaohsiung Ports are presented in Tables 1, 2, and 3, respectively. We observed that the monthly time-series data for each port exhibited a seasonal pattern. The sharp reduction in throughput volume in February every year

Table 4. Predicted container throughput at Keelung Port obtained using the classical decomposition model

t	Y_t	12 MA	CMA $=TR_t*CL_t$	SN_t*IR_t	SN_t	$TR'_t=Y_t/SN_t$	$\hat{TR}_t$ =a+bt	$\hat{Y}_t=\hat{TR}_t\times SN_t$
1	113,548				1.025	110818	120125	123085
2	73,865				0.739	99973	119490	88285
3	115,607				1.009	114574	118854	119925
4	108,000				1.004	107611	118218	118645
5	115,458				1.058	109179	117582	124344
6	117,794	113014.667			1.017	115842	116946	118916
7	119,445	113535.750	113275.208	1.054	1.047	114042	116310	121820
8	117,279	114587.167	114061.458	1.028	1.020	115024	115674	117942
9	114,673	115126.500	114856.833	0.998	0.975	117567	115038	112206
10	119,768	115862.000	115494.250	1.037	1.030	116249	114402	117865
11	117,972	116410.750	116136.375	1.016	1.018	115891	113766	115810
12	122,767	117014.000	116712.375	1.052	1.059	115934	113130	119799
13	119,801	117401.250	117207.625	1.022	1.025	116920	112495	115266
14	86,482	117579.083	117490.167	0.736	0.739	117050	111859	82646
15	122,079	117405.417	117492.250	1.039	1.009	120988	111223	112226
16	116,826	117184.500	117294.958	0.996	1.004	116406	110587	110986
17	122,043	117258.167	117221.333	1.041	1.058	115406	109951	116274
18	125,033	116943.667	117100.917	1.068	1.017	122962	109315	111157
19	124,092	116498.500	116721.083	1.063	1.047	118479	108679	113828
20	119,413	116191.333	116344.917	1.026	1.020	117117	108043	110161
21	112,589	114305.083	115248.208	0.977	0.975	115430	107407	104763
22	117,117	112830.333	113567.708	1.031	1.030	113676	106771	110003
23	118,856	111564.417	112197.375	1.059	1.018	116759	106135	108042
24	118,993	109164.333	110364.375	1.078	1.059	112370	105499	111718
25	114,459	107209.917	108187.125	1.058	1.025	111707	104864	107447
26	82,796	105349.917	106279.917	0.779	0.739	112061	104228	77008
27	99,444	103566.500	104458.208	0.952	1.009	98555	103592	104526
28	99,129	101965.333	102765.917	0.965	1.004	98772	102956	103328
29	106,852	99843.750	100904.542	1.059	1.058	101041	102320	108204
30	96,232	98230.500	99037.125	0.972	1.017	94638	101684	103397
31	100,639	96552.333	97391.417	1.033	1.047	96087	101048	105835
32	97,093	95173.417	95862.875	1.013	1.020	95226	100412	102381
33	91,188	94988.250	95080.833	0.959	0.975	93489	99776	97320
34	97,903	94886.167	94937.208	1.031	1.030	95027	99140	102141
35	93,397	94307.333	94596.750	0.987	1.018	91749	98504	100274
36	99,634	94446.000	94376.667	1.056	1.059	94088	97869	103637
37	94,321	93732.417	94089.208	1.002	1.025	92053	97233	99628
38	66,249	93501.250	93616.833	0.708	0.739	89665	96597	71370
39	97,222	92653.000	93077.125	1.045	1.009	96353	95961	96826
40	97,904	92300.333	92476.667	1.059	1.004	97552	95325	95669
41	99,906	92475.583	92387.958	1.081	1.058	94473	94689	100134
42	97,896	92593.917	92534.750	1.058	1.017	96274	94053	95638
43	92,076				1.047	87911	93417	97843
44	94,319				1.020	92506	92781	94600
45	81,009				0.975	83053	92145	89877
46	93,671				1.030	90919	91509	94279
47	95,500				1.018	93815	90874	92506
48	101,054				1.059	95429	90238	95556
49	83,740				1.025		89602	91809
50	76,935				0.739		88966	65732

Table 4. (Continued)

t	Yt	12 MA	CMA =TRt *CLt	SNt*IRt	SNt	TR'_t =Yt/SNt	$\hat{TR}_t$ =a+bt	$\hat{Y}_t = \hat{TR}_t \times$ SNt
51	99,461				1.009		88330	89126
52	95,803				1.004		87694	88011
53	100,014				1.058		87058	92065
54	98,313				1.017		86422	87878
55	95,665				1.047		85786	89850
56	98,846				1.020		85150	86819
57	98,301				0.975		84514	82434
58	95,011				1.030		83878	86417
59	104,848				1.018		83243	84738
60	104,457				1.059		82607	87476

for all three ports can be attributed to the ports closing due to the Chinese New Year holidays.

2. Results for the models

This section presents the results obtained from all six models. Due to word count limitations, we only reported results for the Keelung Port below. While similar results for the two other ports are not presented here, the evaluations of their forecasting performance are provided in the next section.

1) Classical decomposition model

Based on the classical decomposition model discussed in Section 3.1, we summarized the results for Keelung Port in Table 4.

2) Trigonometric regression model

We estimated Equation (4) using the SAS statistical software and obtained the following results:

$$\hat{y} = 121969 - 662.64875\,t - 11408\,sin\left(\frac{2\pi t}{12}\right) + 267.00044\,t\sin\left(\frac{2\pi t}{12}\right)$$
$$(39.15)\quad(-5.99)\quad(-2.62)\quad(1.7)$$

$$-2420.54374\,cos\left(\frac{2\pi t}{12}\right) + 36.45778\,t\cos\left(\frac{2\pi t}{12}\right) - 6454.68808\,sin\left(\frac{4\pi t}{12}\right)$$
$$(-0.54)\quad(0.23)\quad(-1.49)$$

$$+67.70822\,t\,sin\left(\frac{4\pi t}{12}\right) + 5539.86926\cos\left(\frac{4\pi t}{12}\right) - 0.33531\,t\,cos\left(\frac{4\pi t}{12}\right) \quad (18)$$
$$(0.43)\quad(1.26)\quad(-0.0006)$$

where the numbers in parentheses indicate the t-values of the estimated coefficients. Furthermore, we found that $R^2 = 0.5733$ and adjusted $R^2 = 0.4722$. The variance analysis showed that the F-value for the overall significance of the model was 5.67 with a P-value of 0.0001. This suggests that the model was empirically acceptable. Next, Equation (18) was used to forecast Keelung Port's container throughput for the period January–December 2017. The detailed forecast results are summarized in Table 8.

3) Seasonal dummy regression

Similar to the trigonometric regression model, we estimated Equation (7) by using the SAS statistical package. However, we performed a logarithmic transformation of the time series for the dependent variable before running the regression. The estimation results are reported as follows:

$$\hat{y}_t = b_0 + b_1 t + b_{s1}X_{s1,t} + b_{s2}X_{s2,t} + \ldots\ldots + b_{s11}X_{s11,t}$$

$$= 130606 - 666.46181t - 7410.82986X_{s1,t} - 39929X_{s2,t} - 8022.1562X_{s3,t}$$
$$(29.63)\quad(-8.36)\quad(-1.4)\quad(-7.54)\quad(-1.52)$$

$$-10479X_{s4,t} - 4212.48264X_{s5,t} - 5372.02083X_{s6,t} - 4881.30903X_{s7,t}$$
$$(-1.99)\quad(-0.8)\quad(-1.02)\quad(-0.93)$$

$$-6251.84722X_{s8,t} - 12747X_{s9,t} - 4830.17361X_{s10,t} - 4847.21181_{Xs11,t}$$
$$(-1.19)\quad(-2.43)\quad(-0.92)\quad(-0.93)$$

(19)

where, again, the numbers in parentheses represent the t-values for the coefficient estimates. The F-value for the overall significance of the model was 11.59 with a P-value of 0.0001, while $R^2 = 0.7989$ and adjusted $R^2 = 0.73$. Based on the results reported in Equation (19), we calculated the predicted container throughput values for Keelung Port for the period January–December 2017. The detailed results are listed in Table 8.

4) Grey forecasting model

In the grey model, forecast values are susceptible to the size of the initial sequence of the chosen time series. Therefore, we estimated the grey forecasting model five times with variances in the initial sequence. The lowest prediction errors were found when the initial sequence's size was equal to four. We

Table 5. Class ratio test

2014/1	2015/1	2016/1
0.4866	0.6709	0.7866

Table 6. Accumulated generated sequence

2013/1	2014/1	2015/1	2016/1
113548	233349	347808	442129

Table 7. Mean value generating sequence

2013~2014	2014~2015	2015~2016
173448.5	290578.5	394968.5

Table 8. Actual and predicted container throughput volumes at Keelung Port. Unit: TEUs

	Actual volume	Classical de-compo-sition	Trigonometric model	Seasonal dummy regression	Grey forecast	Hybrid grey	SARIMA(0,1,1)(1,0,0)12 noint
1	83,740	91,809	89830	90538	86,827	92,700	94,364
2	76,935	65,732	84803	57354	60,745	66,378	71,884
3	99,461	89,126	84866	88594	82,958	90,014	96,687
4	95,803	88,011	89701	85471	85,782	88,899	97,233
5	100,014	92,065	93883	91071	88,961	93,006	98,836
6	98,313	87,878	92154	89245	80,815	88,789	97,226
7	95,665	89,850	84638	89069	76,712	90,795	92,566
8	98,846	86,819	76918	87032	80,192	87,745	94,362
9	98,301	82,434	74873	79871	66,887	83,325	83,704
10	95,011	86,417	79283	87121	81,033	87,364	93,843
11	104,848	84,738	85355	86437	80,375	85,679	95,308
12	104,457	87,476	87491	90618	89,269	88,461	99,755

performed the following steps to generate predicted values for the time series using the grey model:

(a) Class ratio test:

The application of the model GM (1, 1) requires that the time-series data first passes the class ratio test. As mentioned in Section 3.4, the value of $\sigma(k)$ must fall between zero and one for the sequence $x^{(0)}$ to fit the grey model. The class ratio test results, shown in Table 5, suggest that the grey model was appropriate for the time series. In general, we used the time-series data to perform the class ratio test. It should be noted that we used the data for the same month of different years to achieve greater forecasting accuracy.

(b) Accumulated generated operation (AGO):

Based on Equation (9), we performed an AGO to obtain the next sequence as shown in Table 6.

(c) Mean value generating sequence

Using Equation (13), we calculated the mean value generating sequence, as shown in Table 7.

(d) Time-series prediction model

Using the least squares method, we obtained estimates for coefficients $\hat{a}$ and $\hat{b}$ as follows:

$$\hat{a} = 0.1136177451$$

$$\hat{b} = 142059.3772476048$$

These estimates were used to obtain

$$\hat{X}^{(0)}(k+1) = \left(1 - e^{\hat{a}}\right)\left[X^{(0)}(1) - \frac{\hat{b}}{\hat{a}}\right]e^{-\hat{a}k} \tag{20}$$

Based on Equation (20), the predicted time series values for

Table 9. Actual and predicted container throughput volumes at Taichung Port. Unit: TEUs

	Actual volume	Classical decomposition	Trigonometric model	Seasonal dummy regression	Grey forecast	Hybrid grey	SARIMA(0,1,1)(1,1,0)12 noint
1	112,304	127,683	102346	106162	122,707	127,882	117,283
2	99,783	100,930	95528	82444	69,902	101,087	99,648
3	120,898	130,712	95934	110943	105,784	130,914	119,141
4	118,855	130,515	102640	106383	109,724	130,715	120,769
5	122,133	129,491	108865	108626	104,252	129,689	118,434
6	118,145	131,078	108756	106652	98,635	131,277	118,206
7	116,973	129,187	103263	107274	105,290	129,382	121,669
8	122,202	131,397	99127	107608	96,282	131,595	119,573
9	112,542	117,308	101905	96273	94,963	117,483	113,927
10	117,756	126,479	109976	107128	126,497	126,667	128,008
11	122,835	129,701	115729	107505	108,824	129,893	124,135
12	134,419	129,817	112961	109064	123,698	130,009	128,777

Table 10. Actual and predicted container throughput volumes at Kaohsiung Port. Unit: TEUs

	Actual volume	Classical decomposition	Trigonometric model	Seasonal dummy regression	Grey forecast	Hybrid grey	SARIMA(0,1,1)(2,0,0)12 noint
1	771,067	742,618	723819	743170	693,889	742,782	747,149
2	679,891	636,134	701692	630850	594,705	636,274	630,437
3	818,258	769,166	719302	767095	761,830	769,335	773,557
4	736,589	769,108	762144	761608	752,605	769,276	754,686
5	750,163	772,161	791362	771047	766,277	772,330	761,544
6	709,266	757,741	781372	748684	734,235	757,907	730,072
7	675,020	758,208	744729	754538	729,701	758,373	723,121
8	738,044	750,844	719450	753037	749,929	751,007	730,335
9	704,586	742,070	731096	727903	652,914	742,231	701,232
10	709,712	773,756	767225	778303	765,209	773,923	732,489
11	733,140	756,268	789911	767291	785,072	756,432	730,080
12	768,306	784,212	774160	789094	792,177	784,381	750,387

the period January–December 2017 were calculated and are presented in Table 8.

(e) Hybrid grey forecast

Following the calculation procedures described in Section 3.5 for the hybrid grey model, we calculated the predicted container throughput of Keelung Port for the period January–December 2017. The detailed results are presented in Table 8.

5) SARIMA model

By examining historical data, we found that seasonality and trends showed the same patterns year after year. Hence, the original series required either a first-order or first-seasonal differencing to produce a stationary series. We utilized the SAS statistical software to determine and estimate the SARIMA model. According to the AIC criterion, the best model for the Keelung Port was SARIMA (0,1,1)(1,0,0)12 noint, which was estimated as follows:

$$\left(1-\mathrm{B}\right)\left(1-\underset{(6.61)}{0.80078}\, B^{12}\right)Z_t = (1+\underset{(4.3)}{0.5441}B)\varepsilon_t \quad (21)$$

where the values in parentheses refer to the t-values for the coefficient estimates. Equation (21) was used to forecast the

Table 11. Performance of various methods of forecasting container throughput at Keelung Port

Forecasting method \ Accuracy measure	MAE	MAPE	RMSE
Classical decomposition	11264.78	11.68	11996.81
Trigonometric model	12959.58	13.32	14408.50
Seasonal dummy regression	11880.75	12.51	12689.08
Grey forecast	16417.60	16.99	17775.80
Hybrid grey	10513.29	10.92	11260.20
SARIMA(0,1,1)(1,0,0)12 noint	4977.75	5.27	6506.14

Table 12. Performance of various methods of forecasting container throughput at Taichung Port

Forecasting method \ Accuracy measure	MAE	MAPE	RMSE
Classical decomposition	8721.33	7.36	9540.83
Trigonometric model	13484.58	11.22	14923.76
Seasonal dummy regression	13565.25	11.45	14347.24
Grey forecast	15881.22	13.68	17122.78
Hybrid grey	8880.83	7.50	9704.91
SARIMA(0,1,1)(1,1,0) 12 noint	3204.05	2.67	4230.32

container throughput of Keelung Port for the SARIMA specification.

3. Comparison of forecasting methods

The predicted container throughput volume was computed using each of the six forecasting methods for the out-of-sample period January—December 2017. Tables 8, 9, and 10 present the results for the Keelung, Taichung, and Kaohsiung Ports, respectively, along with the actual values for comparison.

Yokum and Armstrong (1995) conducted two studies regarding experts' opinions of the criteria utilized to choose forecasting techniques. They found that accuracy was the most critical criterion for most researchers. Since there is no universally accepted measure of accuracy, several criteria are typically used to conduct a comprehensive assessment of forecasting models. The forecasting performance of different models often vary depending on the accuracy measure used (Makridakis et al., 1982). In this study, we selected three criteria, commonly used to measure accuracy, to assess the six forecasting models. These criteria were the root mean squared error (RMSE), the mean absolute error (MAE), and the mean absolute percent error (MAPE), which were defined as follows:

$$MAE = \frac{\sum_{i=1}^{n} \left| Y_i - \hat{Y}_i \right|}{n}, \quad (22)$$

$$MAPE = \frac{100 \sum_{i=1}^{n} \left| \frac{Y_i - \hat{Y}_i}{Y_i} \right|}{n}, \quad (23)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} \left(Y_i - \hat{Y}_i \right)^2}{n}}, \quad (24)$$

where Y_i and $\hat{Y}_i$ are the actual and predicted values, respectively, of the time series in period *i*. Obviously, all three measures were positive in value. Moreover, the smaller the value obtained for each measure, the better the performance of the forecasting method.

The comparison results for the forecasting accuracy of the six methods used to predict the container throughput data for the Keelung, Taichung, and Kaohsiung Ports are presented in Tables 11, 12, and 13, respectively. Table 11 shows that the SARIMA model was clearly the best forecasting model since it had the lowest values for all performance measures. The hybrid grey forecast appeared to be the second-best model in terms of forecast accuracy regardless of which measure was used. There were no significant differences between the classical decomposition, seasonal dummy regression, and trigonometric models. However, the grey forecasting model was revealed as the worst method for predicting container throughput at Keelung Port.

Table 13. Performance of various methods of forecasting container throughput at Kaohsiung Port

Prediction methods \ Error measures	MAE	MAPE	RMSE
Classical decomposition	38403.24	5.32	43208.66
Trigonometric model	45151.33	6.15	52059.63
Seasonal dummy regression	37898.33	5.25	42633.64
Grey forecast	43785.67	6.03	49736.54
Hybrid grey	38488.35	5.34	43280.78
SARIMA(2,0,0)(1,0,0) 12 noint	22606.45	3.11	27597.49

In the case of Taichung Port, Table 12 shows that the SARIMA model showed the best results. The classical decomposition method appeared to be the second-best model, while the hybrid grey forecasting model was ranked third. However, we found that the superiority of the classical decomposition method over the hybrid grey forecasting method was insignificant. They could be considered as having the same predictive capability. Similar to the case of Keelung Port, the grey forecasting model was found to be the worst among all the methods.

In terms of forecasting accuracy, the results for Kaohsiung Port, reported in Table 13, were similar to those for Keelung Port. Regardless of the three measures, the SARIMA model was still the best method. In this case, trigonometric regression was the worst method for forecasting container throughput volume. We noted that the forecasting errors obtained for Kaohsiung Port were, in general, smaller than those observed for other ports.

In forecasting research, no single forecasting model was determined to be the best method in all situations and under all circumstances (Makridakis et al., 1982). Nevertheless, based on the results reported above, we found that, in general, the SARIMA model outperformed other forecasting methods in this study. Thus, the SARIMA model is a reliable method for forecasting container throughput with seasonal variations.

V. CONCLUSIONS

The short-term capacity of a container terminal cannot be increased by adopting different commercial strategies such as throughput inventory keeping, outsourcing, and overtime. Consequently, an important consideration for long-term investment is to understand annual seasonal changes in demand. Therefore, a reliable prediction model is essential to enable terminal operators to make decisions regarding the planning and renovation of building structures and other port facilities (Peng and Chu, 2009).

In this study, six methods, including the classical decomposition, the trigonometric model, the seasonal dummy variables, the grey forecasting, the hybrid grey forecasting, and the SARIMA models, were applied to forecast container throughput based on the monthly data of the Keelung, Taichung, and Kaohsiung Ports. We compared the predictive accuracy of the models by calculating the MAE, MAPE, and RMSE. The SARIMA model provided the most accurate prediction for the Keelung, Taichung, and Kaohsiung Ports in terms of all three accuracy measures.

We compared our results with those of Peng and Chu (2009), who stated that the classical decomposition model was a reliable method for forecasting container throughput with seasonal variations. Contrary to Peng and Chu's results, our study showed that the SARIMA model, which is based on formal statistical theory, was the most suitable method for short-term forecasting. It should be noted that the classical decomposition method is the simplest and easiest method for forecasting container throughput with seasonal variations. It is well-known that sophisticated or complex statistical methods do not necessarily provide more accurate forecasts compared to simpler methods (Makridakis et al., 2000). Thus, the classical decomposition model can be considered as an alternative to the SARIMA model.

The contribution of this research is that it compares the forecasting performance of six univariate methods based on commonly used evaluation criteria, i.e., MAE, RMSE, and MAPE. This study’s outcomes can help to predict near-future demand to understand container throughput at international ports as well as create a reference for appropriate authorities. There are many different industries with diverse characteristics. Likewise, several forecasting methods with different strengths and weaknesses are available. A method optimal for one industry may not be a reliable one for another industry. Therefore, it is of utmost importance to determine the right forecasting method for the industry in question.

The present study can be extended to investigate container throughput volume at other international ports. As a first step in identifying a suitable forecasting method, we recommend that future research examine the distribution of or patterns in data carefully to choose the most appropriate forecasting model. The forecasting performance of various methods depends on the forecasting horizon. Therefore, it is desirable to develop hybrid methods that combine the methods suitable for short-term forecasting with those that are more effective for long-term forecasting (Fildes and Makridakis, 1995).

Thus, in the future, it may be worthwhile to explore other forecasting methods that apply the latest technologies, such as neural networks, artificial intelligence, or advanced data mining techniques, to predict container throughput volumes (Peng and Chu, 2009).

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