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Forecasting container throughput of major Asian ports using the Prophet and hybrid time series models

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ABSTRACT

Forecasting container throughput is critical for improved port planning, operations, and investment strategies. Reliability of forecasting methods need to be ensured before utilizing their outcomes in decision making. This study compares forecasting performances of various time series methods, namely autoregressive integrated moving average (ARIMA), seasonal ARIMA (SARIMA), Holt-Winter's Exponential Smoothing (HWES), and the Prophet model. Since forecast combinations can improve performance, simple and weighted combinations of ARIMA, SARIMA and HWES have been explored, too. Monthly container throughput data of port of Shanghai, Busan, and Nagoya are used. The Prophet model outperforms others in the in-sample forecasting, while combined models outperform others in the out-sample forecasting. Due to the observed differences between the in-sample and out-sample forecast accuracy measures, this study proposes a forecast performance metric consistency check approach for informed real-world applications of forecasting models in port management decision-making.

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1. Introduction

Global container port throughput grew from 46 million twenty-foot equivalent units (TEUs) in 1990 to 200 million TEU in 2022 (Clarksons, 2022). Due to the growing volume, the management of ports has been challenging and complex. Due to capital intensity and risky nature of the investments, ports need to plan the development, operations, and construction of infrastructure according to the throughput development (Chen, Chen, & Li, 2016; Munim, 2020). Port infrastructures having under capacity might lead to reduced competitive positions, whereas exceeding the market demand will result in the loss of productivity. The competitive position of a port is dynamic, which is evident from the changes in the list of top 10 ports in the world over the last 40 years. In 1980, New York/New Jersey was the top port in terms of throughput followed by Rotterdam and Kobe. Hong Kong was the top in 2000 followed by Singapore and Kaohsiung. In 2010, Shanghai was the top followed by Singapore and Hong Kong. In

2021, Shanghai was still the top followed by Singapore and Ningbo-Zhoushan, while Rotterdam was in 10th position and New York/New Jersey not in the list of top 20.¹ Meanwhile, ports throughput growth or decline is one of the core indicators of port performance and the economic development of a country (Munim & Schramm, 2018; Li et al., 2019b). Hence, ports managers are concerned regarding the future port throughput development.

Port planning and development process, from project initialization to final implementation can easily span over 10–20 years depending on the host country context. Regulatory issues as well as financing models play a vital role in port development. Port finances are usually large sums of money with long payback terms due to the nature of the business. Once a decision has been made, cannot be suddenly withdrawn midway; and the success or failure of the investment depends on future port throughput. The same conditions hold to a new port development or a new terminal development within an existing port. Meanwhile, reliable prediction of port throughput development is a complex task. There exists a large variety of forecasting techniques ranging from simple time series

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¹ <https://lloydslist.maritimeintelligence.informa.com/LL1141949/One-Hundred-Ports-The-numbers-tell-the-story>, accessed on February 9, 2023.

models to complex deep network architecture based models (Petropoulos et al., 2022).

In the existing literature, a number of time series models, econometric models, AI-based models, and hybrid models are adopted for container port throughput forecasting (Fiskin & Cerit, 2021; Xie, Zhang, & Wang, 2017). Despite port throughput forecasting has been attracted the widespread interest of practitioners and scholars, there are still some knowledge gaps. Existing studies still lack consensus on accurate forecasting models and a proven guideline to select the right method. Therefore, literature needs further empirical evidence on appropriate model selection guidelines and increasing forecasting accuracy. This study benchmarks forecasting performances of univariate time series methods and proposes a combined model; experiments were conducted for the port of Shanghai, Busan, and Nagoya on monthly container port throughput data. This study reveals different data components that may have an effect on port container throughput and related time series, such as seasonality, hyperparameter optimization algorithm, and forecast error metrics. In order to assess forecasting performance, in-sample and out-of-sample analysis were conducted using different forecast error metrics.

The rest of this study is arranged as follows: in the next section, a literature review is presented which discusses different models for container port throughput. Section 3 outlines the methodology in detail. Section 4 reports and compares the performances of the used methods. Finally, Section 5 presents conclusion and proposes some suggestions for future research.

2. Literature review

Various models have been used to increase the forecasting accuracy of port throughput forecasting over the last couple of decades (Lam, Ng, Seabrooke, & Hui, 2004; Fung, 2001; Geng, Li, Dong, & Liao, 2015; Li, Bai, & Li, 2019). A detailed summary of 20 relevant studies has been reported in Table 4 in the Appendix. Time series models are one of the most frequently preferred models for port throughput forecasting, mostly the ARIMA and its variants, see for example, Geng et al., 2015; Niu, Hu, Sun, & Liu, 2018; Shu, Nguyen, Hsu, Lu, & Huang, 2014. These models forecast future port container throughput utilizing historical trends and have been extensively used as benchmark models in a number of studies. For better forecast performance, some studies have also used exogenous macroeconomic indicators. For instance, Lam et al. (2004) investigated neural network models for forecasting cargo throughput in Hong Kong using several macro-economic and demographic explanatory variables. Similarly, Intihar, Kramberger, and Dragan (2017) investigated the influence of macroeconomic indicators on the accuracy of the container throughput time series forecasting model. However, often it is challenging to have access to data of relevant exogenous variables as most macroeconomic data comes with lags. Additionally, time series and econometric models cannot accurately capture the relationship for dynamic and nonlinear data (Li et al., 2019).

For capturing non-linear characteristics better, AI-based models have attracted increasing interest. Gosasang, Chandraprakasul, and Kiattisin (2011) investigated the neural network method and ordinary least squares (OLS) regression for predicting the container throughput of Bangkok port. The neural network approach, using a multilayer perceptron, was more precise than the OLS regression. Milenković, Milosavljević, Bojović, and Val (2021) proposed a novel approach, a fuzzy ANN (FANN), combined with metaheuristic algorithms. Two novel approaches, Simulated Annealing Fuzzy Artificial Network (SA FANN) and Genetic Algorithm Fuzzy Artificial Neural Network (GA FANN) were explored; ARIMA was used as a benchmark. The GA-FANN outperformed SA-FANN in case of the transit, total, and unloaded container throughput, while SA-FANN

performed better for loaded and empty container throughput. Tang, Xu, and Gao (2019) recommended Back Propagation Neural Network (BPNN) as an optimal forecasting model for container throughput among the Grey model, Holt-Winters Exponential Smoothing (HWES), multiple OLS Regression, and BPNN.

Some of the recent academic contributions seem to be convinced with combining and modifying various forecasting methods and techniques, see for example, (Zhang & Cui, 2011; Xie, Wang, Zhao, & Lai, 2013; Zhang, Huang, & Zhao, 2013; Shu et al., 2014; Du, Wang, Yang, & Niu, 2019). Hybrid models exploit the capacities of multiple models and give a performance boost to forecasting accuracy. Xie et al. (2013) suggested three hybrid approaches based on the least-squares support vector regression (LSSVR) model to overcome the inability of traditional models of capturing non-linearity. Shu et al. (2014) presented the Fourier modified SARIMA models and comprehensively compared with the prediction performance of traditional ARIMA, Grey, and Fourier modified models. The precision of forecasts using traditional models combined with Fourier adjustments in residual was significantly better. Zha, Chai, Witlox, and Le (2016) analyzed different combinations of SARIMA and Artificial Neural Network (ANN), and observed that the SARIMA-ANN hybrid model performs better than standalone SARIMA or ANN. Gamassa and Chen (2017) evaluated the Grey model, OLS regression, Holt's trend model, and a combination of these three models and validated these models using container throughput data of Abidjan. The Holt's trend model outperformed the other models with the lowest MAPE. Chen et al. (2016) used a hybrid model combining the Pearl Curve model, GM(1,1) model, and DES model to optimize the port cargo throughput forecast of the Dalian port and found that the combined model performed better than single models. For other relevant applications of ports throughput forecasting approaches, see Gao, Luo and Zou (2016), Rashed, Meersman, Sys, Van de Voorde, and Vanelander (2018), Chan, Xu, and Qi (2017), Shankar, Ilavarasan, Punia, and Singh (2020), and Sanguri, Shankar, Punia, and Patra (2022).

This study forecasts port throughput of Shanghai, Busan and Nagoya ports using the ARIMA, SARIMA, HWES, and Prophet models. Although the first three models have been explored in the literature already, to the best of the authors' knowledge, the Prophet model is being used for the first time in port throughput forecasting context. Further, this study proposed combined forecasting models with different optimized parameters.

3. Methodology

ARIMA, SARIMA, HWES, the Prophet model, and combined models have been implemented for container throughput forecasting in this study.

3.1. ARIMA

The Box and Jenkins (1976) ARIMA model is one of the most widely applied methods in time series forecasting. ARIMA model has two components: an autoregression (AR) and a moving average (MA) part. When a time series is stationary in difference operator, then, an ARIMA (p, d, q) model is expressed by Eq. (1). Here, p is the order of the AR part, d is the number of differencing, and q is the order of the MA part. An ARIMA model in first difference is denoted with (p,1,q).

$$y'_t = \sum_{i=1}^p \phi_i y'_{t-i} + \sum_{i=1}^q \theta_i \varepsilon_{t-i} + \varepsilon_t \quad (1)$$

Here, y'_t is the differenced port throughput at time t, ϕ_i is the coefficient of y'_{t-i} , θ_i is the coefficient of MA error terms (ε_{t-i}) at time t-1, and ε_t is the residual at time t.

3.2. SARIMA

SARIMA is an extension of the original ARIMA model with seasonal components. SARIMA model has total six components grouped into two: (p, d, q), and (P, D, Q), which refer to the non-negative integers of the polynomial order of the AR, integrated (I), and MA parts of the non-seasonal and seasonal components of the SARIMA, respectively (Vagropoulos, Chouliaras, Kardakos, Simoglou, & Bakirtzis, 2016). SARIMA (p, d, q)(P, D, Q)s model can be expressed by Eq. (2).

$$\varphi_p(B)\Phi_P(B^s)\nabla^d\nabla_s^D y_t = \theta_q(B)\Theta_Q(B^s)\varepsilon_t \quad (2)$$

y_t is the stationary port throughput at time t ; $\varphi_p(B)$ is the non-seasonal AR polynomial of order p , $\Phi_P(B^s)$ is the seasonal AR polynomial of order P , $\theta_q(B)$ and $\Theta_Q(B^s)$ are the non-seasonal and seasonal MA polynomial of order q and Q , respectively. ∇^d and ∇_s^D are the non-seasonal and seasonal difference operators, respectively. B is the backshift operator, ε_t indicates residuals and s indicates number of seasonal periods.

3.3. HWES

The Exponential smoothing model was introduced in the late 1950s (Holt, 1957; Winters, 1960). HWES postulate that forecasts can be generated based on past data points with weights declining exponentially as the data points get older. A simple exponential smoothing model can be utilized for forecasting data points without any clear trend or seasonality. To handle time series with trends, Holt's trend or the Double Exponential Smoothing (DES) was proposed, and later the Holt-Winter's Exponential Smoothing (HWES) to capture the seasonality component as well. There are two forms of the HWES approach: additive and multiplicative (Hyndman & Athanasopoulos, 2018). They differ in the nature of the seasonal element. When the seasonal variations are approximately constant, additive approach can be used. On the other hand, with seasonal variations changing proportionally to the level of a time series, multiplicative approach can be used. In addition, both additive and multiplicative methods can be extended with the inclusion of the dampening parameter (Hyndman & Athanasopoulos, 2018).

The HWES additive method can be expressed as follows:

$$\hat{y}_{t+h|t} = [l_t + hb_t] + s_{t+h-m(k+1)} \quad (3)$$

$$l_t = \alpha(y_t/s_{t-m}) + (1 - \alpha)(l_{t-1} + b_{t-1}) \quad (4)$$

$$b_t = \beta^*(l_t - l_{t-1}) + (1 - \beta^*)b_{t-1} \quad (5)$$

$$s_t = \gamma(y_t - l_{t-1} + b_{t-1}) + (1 - \gamma)s_{t-m} \quad (6)$$

The HWES multiplicative method can be expressed as follows:

$$\hat{y}_{t+h|t} = [l_t + hb_t]s_{t+h-m(k+1)} \quad (7)$$

$$l_t = \alpha(y_t/s_{t-m}) + (1 - \alpha)(l_{t-1} + b_{t-1}) \quad (8)$$

$$b_t = \beta^*(l_t - l_{t-1}) + (1 - \beta^*)b_{t-1} \quad (9)$$

$$s_t = \gamma \frac{y_t}{(l_{t-1} + b_{t-1})} + (1 - \gamma)s_{t-m} \quad (10)$$

The HWES damped approach with multiplicative seasonality can be expressed as follows:

$$\hat{y}_{t+h|t} = [l_t + (\phi + \phi^2 + \dots + \phi^h)b_t]s_{t+h-m(k+1)} \quad (11)$$

$$l_t = \alpha(y_t/s_{t-m}) + (1 - \alpha)(l_{t-1} + \phi b_{t-1}) \quad (12)$$

$$b_t = \beta^*(l_t - l_{t-1}) + (1 - \beta^*)\phi b_{t-1} \quad (13)$$

$$s_t = \gamma \frac{y_t}{(l_{t-1} + \phi b_{t-1})} + (1 - \gamma)s_{t-m} \quad (14)$$

here l_t indicates an estimate of the level of the series at time t , b_t denotes an estimate of the trend (slope) of the series at time t , α is the smoothing parameter for the level, s_t is the seasonal component, α , β^* , γ are the corresponding smoothing parameters, m indicates the period of the seasonality, k is the integer part of $(h - 1)/m$. In this study, the possible combinations of these variations were investigated, and models performing best based on AIC and MAPE were chosen (see Table 5 in the Appendix).

3.4. PROPHET

The prophet is an open-source forecasting model developed by the Facebook. The prophet integrates an additive model where non-linear trends can be integrated with time-varying seasonality effects of weekly and daily data as well as holiday effects. Prophet is usually robust to missing data points and outliers (Taylor & Letham, 2018). Prophet decomposes a time series with three core components: trend, seasonality, and holidays, which can be expressed as follows:

$$y(t) = g(t) + s(t) + h(t) + \varepsilon_t \quad (15)$$

Here, $g(t)$ is the trend function, $s(t)$ represents the periodic seasonal effects, $h(t)$ the holiday effects, and ε_t the residuals.

3.5. Forecast combinations

Bates and Granger (1969) presented a promising option for using an individual forecasting method in the form of a combination forecast. Combining forecasts basically refers to the averaging of different independent forecasts (Armstrong, 2001). The motivation behind the idea of combining forecasts stems from a simple portfolio diversification argument. Various combination strategies ranging from simple mean to more complex methods such as neural networks or Bayesian model averaging methods are discussed in the literature. Yang (2004) suggests that different combining methods can be classified into two major classes based on their goal, namely combination for improvement, and combination for adaptation. Combination for improvement is finding the best linear combination of a set of forecasts. This can be achieved by using methods to minimize the residual variance of the combination (Sánchez, 2008). Combination for adaptation aims to perform at least as good as the best individual method.

Armstrong (2001) suggests using at least five forecasts when possible to get a better result and warns that adding more methods leads to diminishing rates of improvement. There is no consensus in the literature that more sophisticated combining strategies might be superior to simple averaging methods (Armstrong, 2001; Yang, 2004; Hibon & Evgeniou, 2005). Hyndman and Athanasopoulos (2018) stresses the performance of simple average methods for combining forecasts is on par with other sophisticated methods. In this study, simple averaging and weighted average methods are utilized. A simple averaging method is shown below:

$$\hat{y}_t = \frac{1}{n} \sum_{i=1}^n \hat{y}_i \quad (16)$$

Here, \hat{y}_t is the combined point forecast, n is the number of component models, \hat{y}_i is the point forecast generated by i 'th model.

The weighted average model can be represented mathematically as follows:

$$\hat{y}_t = \frac{1}{n} \sum_{i=1}^n w_i \hat{y}_i \quad (17)$$

Here w_i is the assigned weight to the i 'th model.

Three different forecasts generated by three different techniques namely, ARIMA, SARIMA, and HWES have been combined using a simple averaging and weighted average approach. For the simple average approach, each forecast was provided equal weights; while for the weighted average method, weights were identified by employing an optimization algorithm that identifies the weight for each forecast which generates a minimum MAPE or AIC value for the combination forecast. The range of the weights chosen is from 0.01 to 0.99.

3.6. Model assessment

Considering the most widely used metrics (see Table 4 in the Appendix), four performance metrics or forecasting accuracy measures are used to assess the performance of a forecasting technique. MSE, RMSE, and MAE are frequently used scale-dependent measures, while MAPE is based on percentage errors and is widely used to compare forecast performance of multiple models (Hyndman & Koehler, 2006). The MAE, MSE, RMSE, and MAPE can be mathematically expressed as follows:

(1) MSE

$$MSE = \text{mean}(\varepsilon_t^2) \quad (18)$$

(2) RMSE

$$RMSE = \sqrt{\text{mean}(\varepsilon_t^2)} \quad (19)$$

(3) MAE

$$MAE = \text{mean}(|\varepsilon_t|) \quad (20)$$

(4) MAPE

$$MAPE = \text{mean}(|p_t|) \quad (21)$$

Here, Y_t denote the ports throughput at time t , and F_t the forecast of Y_t , $\varepsilon_t = Y_t - F_t$, $p_t = 100\varepsilon_t/Y_t$.

4. Data and results

4.1. Data

The port of Shanghai, an international hub port is located at the estuary of the Yangtze River Delta in China (Niu et al., 2018) and it is the world's largest container port in 2021 with a 47.03 million TEU throughput.² Busan is one of the transshipment giants outside of China and the world's seventh busiest port in 2021 with a 22.71 million TEU throughput.³ Port of Shanghai and Port of Busan are two of the most investigated ports in terms of their competitiveness (Luo, Chen, & Zhang, 2022). Port of Nagoya is situated at the center of the Japanese Archipelago on the east coast and one of the busiest ports in Japan in terms of containerized trade with 2.73 million TEU (Nagoya Port Authority, 2022). Based on the importance and impact of port of Shanghai, Busan, and Nagoya in the East Asia region, this study focused on port throughputs of these port. For analysis, monthly container throughput data from January 2010 till December 2019 were used, and data extracted from the respective port's website. For the three port, a total of 120 observations were available, of which, the first 96 data points from January 2010 till December 2017 are used as training or in-sample data, and the remaining 24 data points from January 2018 to December 2019 are used as test or out-sample data. The test dataset is used to validate

Table 1

Descriptive Statistics and ADF test results.

	Nagoya	Shanghai	Busan
Observations	120.00	120.00	120
Mean	225342.83	3013433.33	1555558.33
Standard Deviation	16115.11	426000.23	207367.32
Minimum	181585.00	1870000.00	1013000.00
Maximum	262470.00	3855000.00	1931000.00
25 %	216438.50	2727000.00	1414750.00
50 %	225610.50	3001000.00	1585500.00
75 %	262470.00	3324750.00	1698000.00
Before differencing			
After differencing by lag 1			
Shanghai	ADF	-0.0348	-3.282
	Statistic		
	p-value	0.955	0.015
	Critical Values		
	1 %	-3.494	-3.494
Busan	5 %	-2.889	-2.889
	10 %	-2.582	-2.582
	ADF	-2.262	-3.057
	Statistic		
	p-value	0.184	0.029
Nagoya	Critical Values		
	1 %	-3.494	-3.494
	5 %	-2.889	-2.889
	10 %	-2.582	-2.582
	ADF	-1.139	-3.717
	Statistic		
	p-value	0.699	0.003
	Critical Values		
	1 %	-3.494	-3.494
	5 %	-2.889	-2.889
	10 %	-2.582	-2.582

the performance of selected forecasting models based on analysis of the training datasets.

4.2. Forecast results

The data analysis and visualizations were performed in Python API, version 3.8.3 with five libraries: Pandas, Numpy, Matplotlib, statsmodels, and prophet. Descriptive statistics of the data are presented in Table 1. To check the stationarity of the training sample, the Augmented Dickey-Fuller (ADF) test was used. The original data of the three time series are found non-stationary, and p-values of the ADF test are greater than the 0.05 statistical significance level. The ADF statistic value is larger than the critical values at a statistical significance level of 0.05, which also supports that the given series are non-stationary. The ADF test result after differencing the original series at first difference confirms stationary. Following the stationarity test results, the autocorrelation function (ACF) and partial autocorrelation function (PACF) of the three series are reported in Appendix B.

In this study, for out-sample forecasting, the dynamic forecasting approach is adopted with a forecast horizon of 2 years. Dynamic approach uses the previously forecasted value in place of the actual value in computing the forecast for the subsequent observation in the time series. Further, ARIMA, SARIMA, HWES, and combined model selections were based on the lowest Akaike Information Criterion (AIC) and lowest MAPE. ARIMA, SARIMA, HWES, and combined model properties are presented in Table 2.

For the ARIMA model, the conditional sum of squares and maximum likelihood estimation (CSS-MLE) are used as the default estimators. Similarly, for the SARIMA model, limited-memory Broyden-Fletcher-Goldfarb-Shanno (L-BFGS) is used as the default solver. For the HWES model, limited memory L-BFGS with box constraint is used as the default minimizer for estimation.

Table 2 provides the models' performance for each port. One of the first observations is that, majority of the experimented models

² <https://lloydlist.maritimeintelligence.informa.com/LL1141509/01-Shanghai-China>, accessed on Feb 09, 2023.

³ <https://lloydlist.maritimeintelligence.informa.com/LL1141516/07-Busan-South-Korea>, accessed on Feb 09, 2023.

Table 2
Forecasting performances of the benchmarked models.

MODELS			In Sample Performance				Out of Sample Performance			
Model Specification			MAE	MSE	RMSE	MAPE	MAE	MSE	RMSE	MAPE
Port of Shanghai										
Naive			190600.000	83298326315.790	288614.494	7.146	209541.667	105318958333.333	324528.825	6.172
ARIMA	AIC	(3,1,11)	118988.440	26319205879.519	162231.951	4.488	168508.429	59237835750.998	243388.241	5.065
	MAPE	(3,0,10)	141969.999	36129978587.960	190078.875	5.304	139856.267	42633583598.683	206479.015	4.207
SARIMA	AIC	(2,1,4)x(3,1,4)	172265.870	118617460892.310	344408.857	6.586	164045.096	43056338051.059	207500.212	4.730
	MAPE	(2,1,4)x(4,1,4)	157687.540	110985620107.503	333145.044	6.034	122700.563	26597207887.299	163086.504	3.556
HWES	AIC	(A,F,M,12,T,T)	65461.590	7630455223.817	87352.477	2.358	108528.270	17091644525.291	120735.016	3.061
	MAPE	(A,F,M,12,F,F)	67072.336	7705380874.717	87780.298	2.410	98304.806	17305825138.102	131551.606	2.821
PROPHET			55259.863	5275133424.585	72.630.114	1.970	143713.775	39237053964.716	198083.452	4.161
COMBINED	Simple	[0.33,0.33,0.33]	88587.136	14256844434	119402.03	3.292	99734.755	18424606700.139	135737.271	2.914
(A,S,H) MAPE	Weighted	[0.19,0.01,0.8]	77084.973	9576112136.990	97857.612	2.772	9434.694	15275825884.622	123595.412	2.734
COMBINED	Simple	[0.33,0.33,0.33]	86464.762	15953677452.225	126307.868	3.206	117655.548	23709626598.325	153979.306	3.414
(A,S,H) AIC	Weighted	[0.19,0.01,0.8]	65328.350	7685671248.780	87667.960	2.378	106253.063	17134502836.224	130898.827	2.992
Port of Busan										
Naive			62147.368	7811536842.105	88382.899	4.255	78083.333	8758583333.333	93587.303	4.293
ARIMA	AIC	(1,1,1)	54758.400	5271493564.261	72605.052	3.802	52783.798	5039849982.627	70991.901	2.939
	MAPE	(4,1,5)	51789.735	4400529944.438	66336.490	3.601	47543.546	4289652698.786	65495.440	2.649
SARIMA	AIC	(2,1,0)x(2,1,1)	71957.721	24727690318.744	157250.406	5.346	133404.481	23672372529.613	153858.287	7.357
	MAPE	(2,1,4)x(2,1,0)	75307.553	25766663054.871	160519.977	5.629	47753.893	3503798845.354	59192.895	2.645
HWES	AIC	(A,T,A,12,F,F)	32108.934	1861709734.329	42147.535	2.159	61826.790	5517833228.076	74282.120	3.367
	MAPE	(A,F,A,12,F,F)	32216.814	1902407148.814	43616.593	2.187	34597.190	2711704489.204	52074.030	1.900
PROPHET			29094.090	1377157350.645	37110.071	1.976	67707.763	7852844383.389	88616.276	3.659
COMBINED	Simple	[0.33,0.33,0.33]	41241.006	3613658169.803	60113.710	2.888	36652.403	2722676444.760	52179.272	2.030
(A,S,H) MAPE	Weighted	[0.01,0.09,0.9]	32665.173	1975628788.327	44448.046	2.219	34484.843	2627587764.200	51260.002	1.898
COMBINED	Simple	[0.33,0.33,0.33]	40976.825	3519729968.457	59327.312	2.851	47937.115	3858663691.635	62118.143	2.661
(A,S,H) AIC	Weighted	[0.04,0.25,0.71]	34712.653	2410026834.203	49092.024	2.372	36123.059	2792920658.059	52848.090	1.995
Port of Nagoya										
Naive			15012.600	362468599.905	19038.608	6.805	13296.583	285366615.333	16892.798	5.619
ARIMA	AIC	(6,1,4)	8162.160	116135657.880	10776.626	3.737	7965.927	103738446.549	10185.207	3.367
	MAPE	(6,1,5)	7860.669	116363312.961	10787.183	3.611	7570.392	99964598.326	9998.230	3.179
SARIMA	AIC	(2,1,4)x(0,1,4)	13032.099	964169262.710	31051.075	6.214	15778.577	363793425.662	19073.370	6.710
	MAPE	(5,1,3)x(0,1,2)	13462.486	939929713.514	30658.273	6.296	6541.264	62990075.787	7936.629	2.723
HWES	AIC	(N,T,A,12,F,F)	6559.660	72107552.455	8491.617	2.955	8871.223	109156561.973	10447.800	3.687
	MAPE	(M,T,A,12,F,F)	7374.229	93716361.786	9680.721	3.329	8140.491	106428006.854	10316.400	3.415
PROPHET			5810.971	54520261.443	7383.784	2.616	15458.989	369854229.706	19231.595	6.428
COMBINED	Simple	[0.33,0.33,0.33]	7784.062	137840256.332	11740.539	3.575	6263.071	71370378.619	8448.099	2.607
(A,S,H) MAPE	Weighted	[0.19,0.8,0.01]	10350.559	408084114.218	20201.092	4.809	6068.237	61174526.047	7821.415	2.516
COMBINED	Simple	[0.33,0.33,0.33]	7263.101	131364955.152	11461.455	3.346	7888.773	103696157.318	10183.131	3.339
(A,S,H) AIC	Weighted	[0.58,0.01,0.41]	6723.887	785917117.666	8865.197	3.064	6893.292	69090899.892	8312.094	2.873

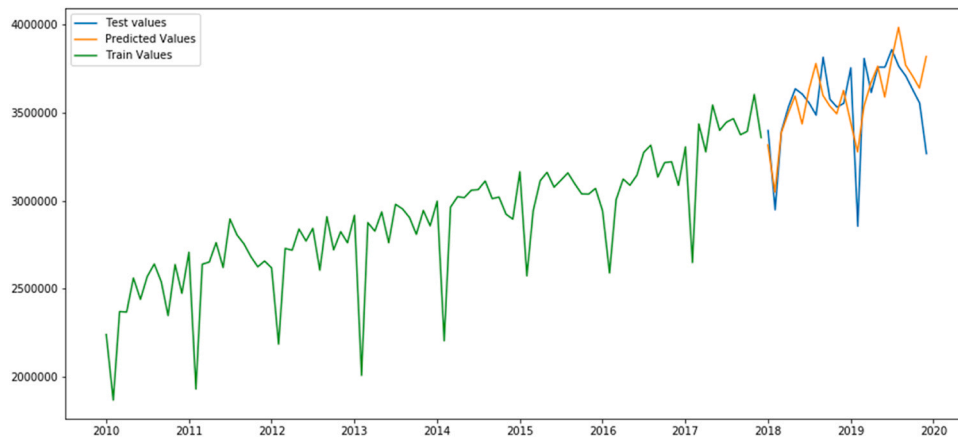
outperforms the naïve forecasts. The average performance of the forecasting models across each port is reported in Table 3. Overall, the Prophet model provides the most accurate in-sample forecast followed by HWES, ARIMA, and SARIMA for the three ports based on the selected error metrics. For the out-of-sample forecast, Prophet produced relatively poor forecasts. For out-of-sample forecasts, a combined forecast using the weighted average method produces the most accurate forecast for the three series based on all error metrics, followed by HWES. HWES method seems to be more precise than ARIMA and SARIMA with few exceptions for both in-sample and out-of-sample forecasts.

For Shanghai, the Prophet produces the most accurate in-sample forecast, while the combined forecast using the weighted average method that combines forecasts produced by the MAPE-optimized component model provides the most accurate out-of-sample forecast. The second best out-of-sample forecast for Shanghai is produced by HWES_MAPE based on MAPE (2.82 %) and MAE (98304.81), followed by other versions of combined forecast methods. While based on RMSE and MSE, HWES_AIC performed a bit better than HWES_MAPE. Both HWES produced the best result with the additive trend and multiplicative seasonality with no damping. ARIMA_AIC produced the worst out-of-sample forecast. One of the interesting

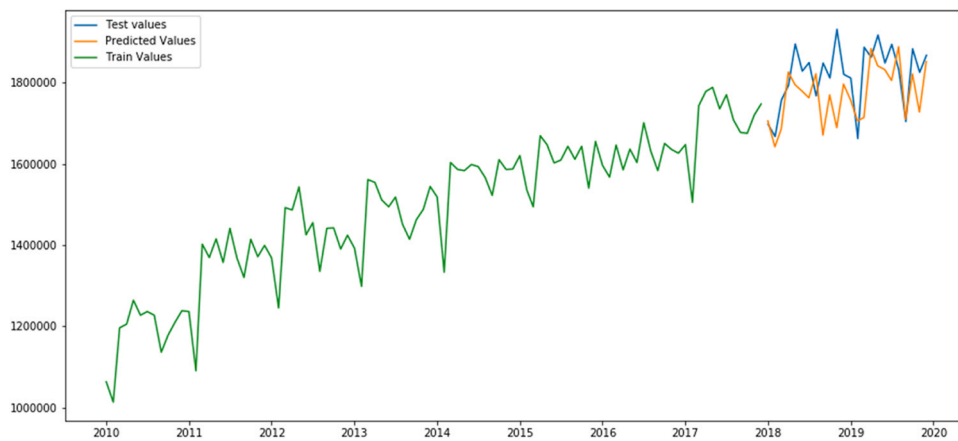
Table 3
Average Performance of the Forecasting Models.

Model		In Sample Performance				Out of Sample Performance				MAPE Difference
		MAE	MSE	RMSE	MAPE	MAE	MSE	RMSE	MAPE	
ARIMA	AIC	60636.333	10568945033.887	81871.210	4.009	76419.385	21460474726.725	108188.450	3.790	0.219
	MAPE	67206.801	13548957281.786	89067.516	4.172	64990.068	15674400298.598	93990.895	3.345	0.827
SARIMA	AIC	85751.897	48103106824.588	177570.113	6.049	104409.385	22364168002.111	126810.623	6.266	0.217
	MAPE	82152.526	45897404291.963	174774.431	5.986	58998.573	10054665602.813	76738.676	2.975	3.012
HWES	AIC	34710.061	3188090836.867	45997.210	2.491	59742.094	7572878105.113	68488.312	3.372	0.881
	MAPE	35554.460	3233834795.106	47025.871	2.642	47014.162	6707985878.053	64647.345	2.712	0.070
PROPHET		30054.975	2235603678.891	22246.928	2.187	75626.842	15819917525.937	101977.108	4.749	2.562
COMBINED (A,S,H) MAPE	Simple	45870.735	6002780953.378	63752.093	3.252	47550.076	7072884507.839	65454.881	2.517	0.735
	Weighted	40033.568	3986608346.512	54168.917	3.267	16662.591	5988196058.290	60892.276	2.383	0.884
COMBINED (A,S,H) AIC	Simple	44901.563	6534924125.278	65698.878	3.134	57827.145	9223995482.426	75426.860	3.138	0.004
	Weighted	35588.297	3627205066.883	48541.727	2.605	49756.471	6665504798.058	64019.670	2.620	0.015

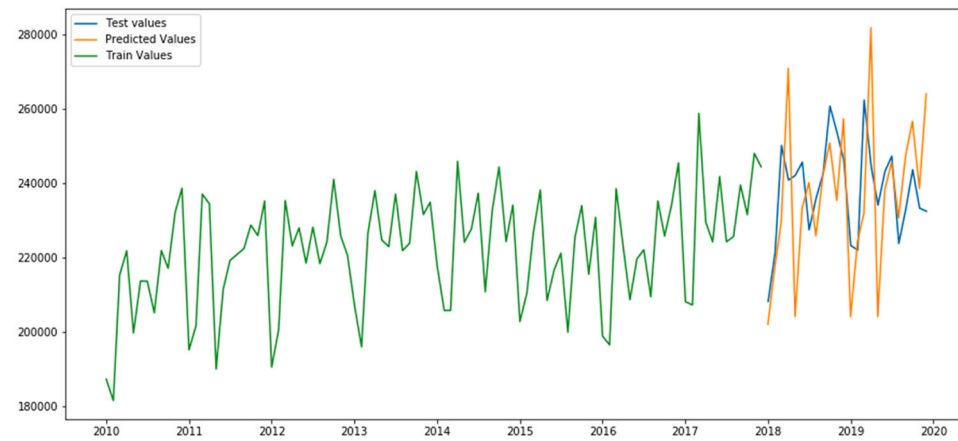
Lowest MAPE difference does not indicate better performance, but only the model performance is consistent in the in-sample and out-sample forecasting.



(a) Shanghai

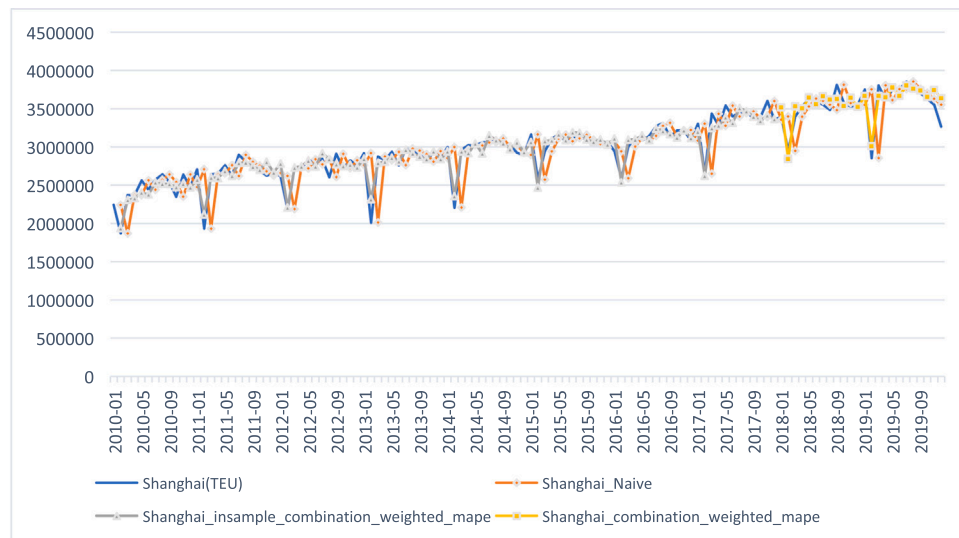


(b) Busan



(c) Nagoya

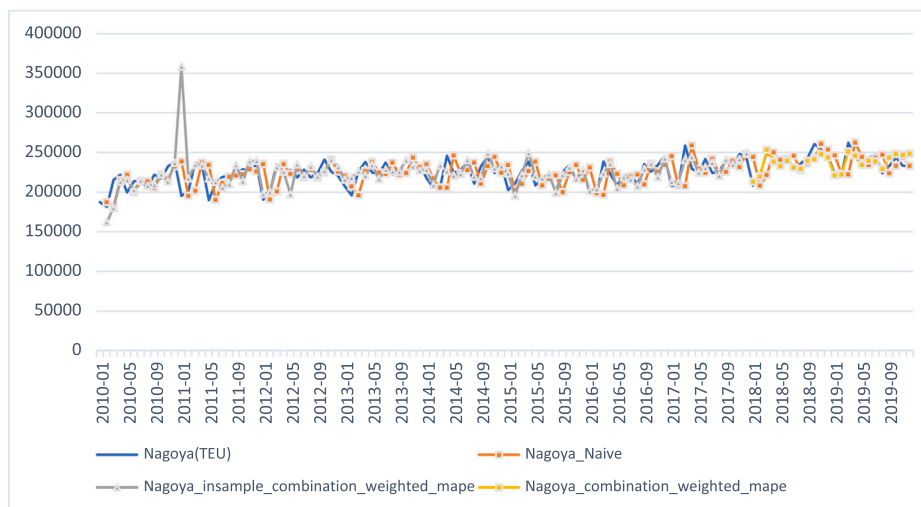
Fig. 1. In-and-out-of-sample port throughput forecasting using the Prophet model.



(a) Shanghai



(b) Busan



(c) Nagoya

Fig. 2. In-and-out-of-sample port throughput forecasts using the Combined Weighted MAPE model.

observations from the experiments is that error metrics used for HWES models are showing contradictory results. HWES_AIC performs better in terms of MSE and RMSE, whereas HWES_MAPE outperforms in terms of MAE and MAPE. This observation further substantiates the need for multiple error metrics while evaluating the forecasting models.

For Busan, Prophet has a superior in-sample forecast based on all the error metrics, while the most accurate out-of-sample forecast is produced by employing the combined forecast approach. HWES_MAPE is the second-best model based on the RMSE, MAPE, MAE, and MSE and performs almost as accurately as the combined forecast model. Prophet produced a forecast with 3.66 % MAPE, which is significantly better than SARIMA_AIC, but still it is the second-worst performing model.

A similar trend is observed for Nagoya where Prophet is the best performing model for in-sample forecasts, while combination forecast is the outperforming model for out-of-sample forecasts. Unlike Shanghai and Busan HWES did not perform well for Nagoya and stands slightly above prophet and SARIMA_AIC in the ranking.

One of the significant results is that in some cases, out-of-sample performance obtains superior performance compared to in-sample performance such as ARIMA_MAPE, SARIMA_AIC and SARIMA_MAPE for Shanghai. Similar results can be seen in the case of Busan, where all the models except Prophet, that are, SARIMA_AIC and HWES_AIC performed much better in the out-of-sample forecast than in the in-sample forecast. For Nagoya, ARIMA_AIC, ARIMA_MAPE, and SARIMA_MAPE performed better for out-of-sample forecasting than in-sample forecasting.

The combination forecast performed very well for the three series for out-of-sample forecasting. For Shanghai, it assigns 80 % weight to Holt-Winters, while 19 % weight to ARIMA and the remaining 1 % to SARIMA. In the case of Busan, 90 % of the weight is assigned to HWES, 9 % to SARIMA, and 1 % to ARIMA. For Nagoya, the weight distribution is a little different, here 80 % of the weight is assigned to SARIMA, 19 % to ARIMA, and 1 % to HWES. Since the in-sample and out-of-sample forecast performance varies across models, in Table 3, we introduced MAPE difference to examine the stability of a forecast model across both samples. For instance, the most stable model is the combined-AIC model based with simple averaging, although this is not the best performing in terms of accuracy measures.

Figs. 1 and 2 presents the forecasts for three port using the best performing models based on in-sample and out-of-sample performance. Hence, the selected models are the Prophet model and the Combined_Weighted_MAPE model.

5. Conclusion and future research

Reliable forecasts can serve as guidelines for the respective port authorities for making well informed decision about port planning and management. It will help the port authorities to manage the capacity and decide when to invest in infrastructure expansion. This study compared the performance of the three most commonly used time series forecasting methods, that are, ARIMA, SARIMA and HWES with one relatively new forecasting method, that is, the Prophet model. A forecast combination approach was explored too by simple and weighted averaging of parameters.

Appendix A

See Appendix Tables 4 and 5.

This study makes several contributions; firstly, methodologically, it shows that the combined forecast model has better forecasting accuracy for the three ports for out-of-sample data. This research further strengthens the claim by previous researchers (Hibon & Evgeniou, 2005; Zha et al., 2016; Mo et al., 2018) that combined models can harness the capacities of multiple models to generate better results.

Second, among the individual models in out-sample forecasting, SARIMA_MAPE performed best for Nagoya, while for Shanghai and Busan HWES_MAPE performed best. HWES model performed consistently well for both in-sample and out-of-sample forecasts for the three ports as evident from a low MAPE difference score in Table 3. Similarly, the outcome was observed by Gamassa and Chen (2017), where the exponential smoothing model outperformed other models. This shows that SARIMA and HWES are still significant models that can produce good forecasts and facilitate authorities to act accordingly. The Prophet model performs very well based on in-sample performance, while it does not translate well into an out-of-sample performance. From the performance of Prophet, it can be concluded that the best in-sample performance does not always translate into a best out-of-sample performance, which is in line with the findings of Pang and Gebka (2017) and supports the assertion of Peng and Chu (2009) that sophisticated models do not necessarily produce a better forecast.

Finally, for hyper parameter optimization algorithm, it can be concluded that the models optimized for MAPE consistently performed better than the models optimized for AIC values. Furthermore, the majority of the previous literature considered static forecasting approach in the out-of-sample forecast to compare the different forecasting models, while there is few studies on dynamic forecasting. This study attempts to fill this gap by presenting the comparison of models based on their dynamic forecasting performances.

Although, this study benchmarks several forecasting models, future works should focus more on exploring relatively newer methods. For example, more advanced forecasting methods that utilizes deep network architecture such as Neural Basis Expansion Analysis for Time Series (N-BEATS), Deep Autoregressive Recurrent Networks (DeepAR) and Temporal Convolutional Networks (TCN) models. However, these models are best fit for large volume datasets with high frequency. Future port throughput forecasting studies that can utilize daily or weekly interval data should consider these models. The applications of large-scale forecasting experiments for uncertain times such as the financial crises and the COVID-19 periods are worth exploring.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. Ziaul Haque Munim acknowledges financial support from the MARKOM 2020 project of the Norwegian government.

Table 4
Summary of relevant port throughput forecasting studies.

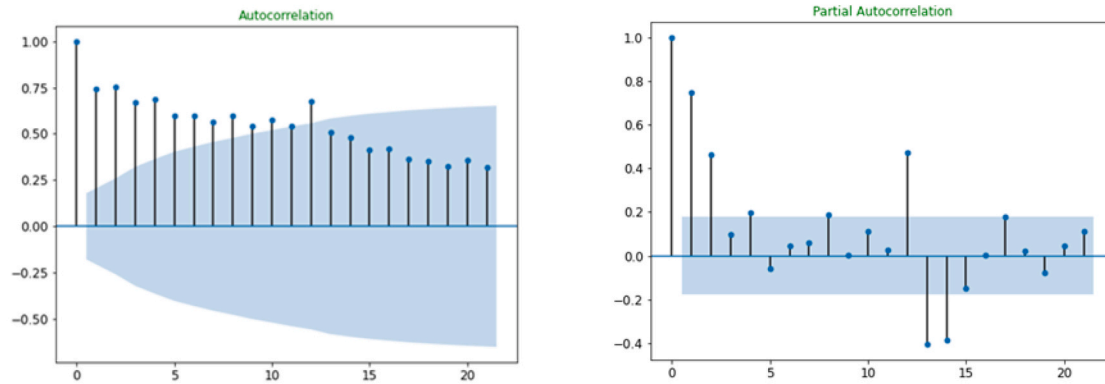
No	Study	Port	Data Type	Number of Observation	Forecast Method	Accuracy Measures	Best Performing Model
1	Gao, Luo, and Zou (2016)	Hong Kong, Shenzhen Singapore, Los-Angeles	Monthly	192	Frequentist MA, Model Averaging Approach LSSVR, ARIMA, SARIMA, X12-A-SAL, X12-M-SAL, X12-M-LSSVR, X12-A-LSSVR, CD-LSSVR, EMD-LSSVR	MSFE, MAPE MAE, MAPE, RMSE, Dstat, DM	Lso_MA X12-M-SAL and X12-A-SAL
2	Xie et al. (2017)		Monthly	265			
3	Pang and Gebka (2017)	Tanjung Priok	Monthly	131	SARIMA, ASHW, MSHW, VECM	MAE, RMSE	MSHW & VECM
4	Rashed, Meersman, Van de Voorde, and Vanelander (2017)	Antwerp	Monthly	243	SARIMA, SARIMA with Intervention, ARIMAX	MAPE	ARIMAX
5	Farhan and Ong (2018)	Antwerp, Buenos Aires, Busan, Callao, Durban Hamburg, Hong Kong, Jeddah, Kaohsiung, Long Beach, Los Angeles, Melbourne, New York, Rotterdam, San Antonio, Santos, Shanghai, Singapore, Veracruz, Yokohama	Monthly	108	SARIMA	MAE, MAPE, WALD TEST	SARIMA
6	Mo et al. (2018)	Xiamen, Shanghai	Monthly	180	SARIMA, SARIMA-BP, SARIMA-GP, SARIMA-SVR, HFMC	MAPE, RMSE, MAE, Dstat	HFMC
7	Rashed, Meersman, Sys, Van de Voorde, and Vanelander (2018)	Antwerp, Zeebrugge, Rotterdam, Le Havre, Hamburg, Bremen	Yearly	28	ARDL	MAPE	ARDL
8	Niu et al. (2018)	Singapore, Shanghai	Monthly	247	VMD-ARIMA-HGWO-SVR, CEEMD-ARIMA-HGWO-SVR, WD-ARIMA-HGWO-SVR, HGWO-SVR, VMD-HGWO-SVR VMD-ARIMA-DE-SVR, VMD-ARIMA-GA-SVR, VMD-ARIMA-GWO-SVR, VMD-ARIMA-CSA-SVR, VMD-ARIMA-PSO-SVR	MSE, MAE, MAPE, CDFR, FVD, DM	VMD-ARIMA-HGWO-SVR
9	Gosasang, Yip, and Chandraprakashkul (2011)	Bangkok	Monthly	192	VECM	MAPE, RMSE, MAE	VECM
10	Du et al. (2019)	Shanghai	Monthly	198	EEEMD-BELM-ECS, VMD-BELM, VMD-BELM-ECS, SARIMA, ELM, LSSVM, ARIMA	MAE, RMSE, MAPE, r, U2(Theil U Statistic 2), IA	VMD-BELM-ECS
11	Chan, Xu, and Qi (2019)	Ningbo zhoushan	Yearly	12	MA, MARS, ARIMA, GM, ANN, SVR	ME, MAE, RMSE, MPE, MAPE	SVR
12	Milenković, Milosavljević, Bojović, and Val (2021)	Barcelona	Monthly	84	ARIMA, Genetic Algorithm ANN, Differential Simulated Annealing	MAE, MAPE, RMSE	GA-ANN
13	Tang et al. (2019)	Lianyungang, Shanghai	Yearly	28	GM, Triple Exponential Smoothing, Multiple Linear Regression, BPNN	MAE, RMSE, MAPE	BPNN
14	Li et al. (2019)	Shanghai, Shenzhen, Guangzhou	Monthly	204	SD BP, SD Elman, SD KELM, SD ELM, SD KELM&ELM, WPD-KELM-ELM, EMD-KELM-ELM, EEEMD-KELM-ELM, CEEMD-KELM-ELM	MAE, RMSE, MAPE, DM, Dstat	SD_KELM & ELM
15	Xie, Qian, and Yang (2019)	Dalian, Tianjin, Qingdao	Monthly	200	MA, HOLT-WINTERS, ARIMA, ANN, LSSVR, EMD-ANN, EMD-LSSVR, W-ANN, W-LSSVR, W-D-AA, W-D-LA	R, d, RMSE, MAE	W-D-LA & W-D-AA
16	Shankar, Ilavarasan, Punia, and Singh (2020)	Singapore	Monthly	287	LSTM, ARIMA, Simple Exponential Smoothing, Holt Winters ES, double Holt Winters ES, Triple Holt Winters ES, Error Trend Seasonality, Trigonometric regressors (TBATS), NN, ARIMA+NN	RME, RAE, RMSE, MAPE	LSTM
17	Eskafi et al. (2021)	Port of Isafjörður, Iceland	Yearly	29	Bayesian method	Not reported	Not applicable
18	Dragan, Keshavarzsaleh, Intihar, Popović, and Kramberger (2021)	Port of Koper, Slovenia	Quarterly	72	DFA-ARIMAX, SARIMA, HW	MAPE, SMAPE, MAAPE, MAE, GMRAE, MdRAE, MBRAE	DFA-ARIMAX
19	Sanguri, Shankar, Punia, and Patra (2022)	Port of Los Angeles, USA	Monthly	324	Hierarchical (ETS, ARIMA, Theta, ANN), ETS, SARIMA, SVM, LSTM, SARIMA-LSTM, SARIMA-SVR	MSE, MAE, RMSE	Hierarchical ETS
20	Huang, Grifoll, Sanchez-Espigares, Zheng, and Feng (2022)	Yangtze River Delta	Monthly	120		MAE, MAPE, and RMSE	SARIMA-LSTM, SARIMA-SVR

Table 5
Specification of HWES models.

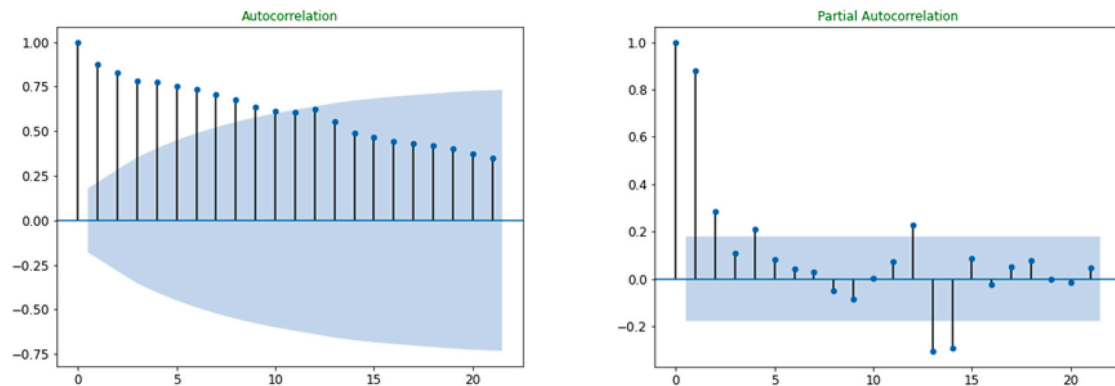
	Optimized for AIC			Optimized for MAPE		
	Shanghai	Busan	Nagoya	Shanghai	Busan	Nagoya
Trend	Additive	Additive	None	Additive	Additive	Multiplicative
Damped	False	True	True	False	False	True
Seasonal	Multiplicative	Additive	Additive	Multiplicative	Additive	Additive
Box-Cox Transform	True	False	False	False	False	False
Remove Bias	True	False	False	False	False	False

Appendix B

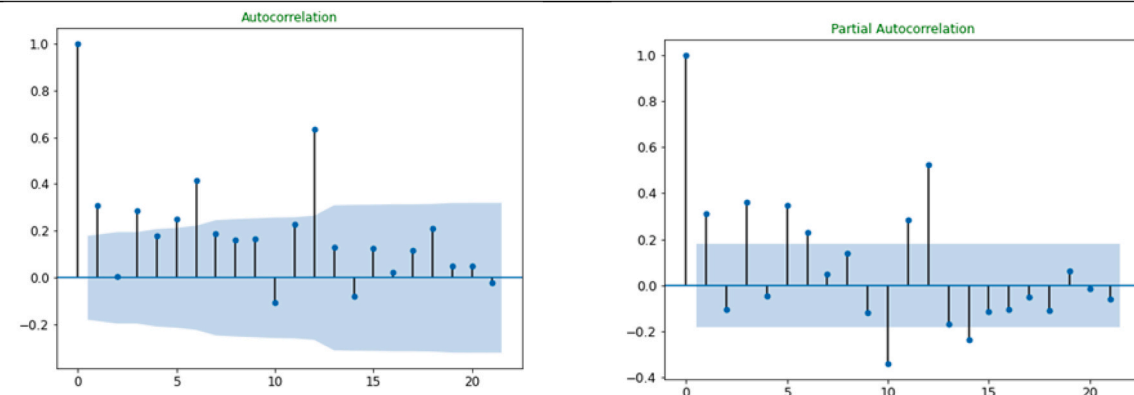
ACF & PACF Plot for port of Shanghai



ACF & PACF Plot for port of Busan



ACF & PACF Plot of port of Nagoya



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