

Univariate Throughput Forecasting Models on Container Terminal Equipment Planning

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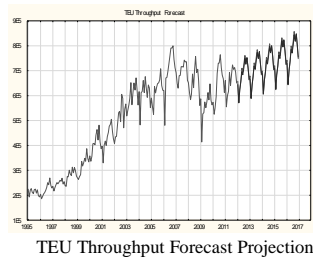
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Graphical abstract



Abstract

Planning of Container Terminal equipment has always been uncertain due to seasonal and fluctuating throughput demand, along with factors of delay in operation, breakdown and maintenance. Many time-series models have been developed to forecast the unforeseen future of container throughput to project the needed amount of port equipments for optimum operation. Conventionally, a "ratio" method developed by port consultants at early port design stage is adopted for equipment planning, giving no consideration to the dynamic growth of the port in terms of improved layout and technological advancement in equipments. This study seeks first to enhance the empirical approach of the equipment planning at the end of planning time horizon by including assumed coefficient of port capacity parameters. The second is to compare the size of equipment purchase by receiving different terminal's future throughput demand from two univariate forecasting models at planning time horizon. The empirical method of equipment planning will be tested against the conventional yard equipment per quay crane ratio after deriving the throughput demand from forecasting models of Holt-Winter's exponential smoothing and seasonal ARIMA (autoregression integrated moving average) model. Results in the form of graphs and tables indicate similar forecasting pattern by two models and equipment estimation proofs to avail more redundancy for optimum operation. Suggestions for better estimation of equipments are also made for future models.

Keywords: Port planning; equipment forecasting; univariate; ARIMA; exponential smoothing

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1.0 INTRODUCTION

Containerization has been an important key in the rapid growth of international trade, particularly for Malaysia as a strategic mid-way-point of the east and west. So, demand has been high on terminals logistics, management and technological breakthrough to be able to service the immense growth of container shipment [1], transshipment or inbound container service. Malaysian ports capacity is one of the most important determinants of meeting the increasing trade.

Port capacity refers to the ability of the port to provide a minimum queuing time, berthing and efficient operation of handling container transfer. An optimum capacity can be defined by various approaches such as economical, theoretical, empirical, operational, engineering or integrated [2].

Container terminals planning is a dynamic system with multiple-aspect consideration to fit for an optimum operation the staggering array of container handling equipment (CHE) that is available. In general, CHE can be categorized into fixed equipments (container conveyer, automated stackers and container lifts), rail-mounted equipments (ship-to-shore cranes, gantries, transtainers and trains) and free-running equipments (rubber-tire-gantry, forklifts, reachstackers, straddle carriers and prime-movers). Inability to match equipment capacity to the handling of

throughput demand may result in long queuing time long after the estimate time of arrival (ETA) and possible hiccups in the loading and unloading process of container from vessel to the respective storage area [3]. Failure to provide service at ETA will impose additional cost and time that may devastate the port's reputation and drive ship-liners away to the nearest adjacent port for a more swift and reliable service. Not only does this cause irreversible investment loss but also the withdrawal of many stakeholders for future investment. [4].

Therefore, substantial planning for additional port equipments, whilst not giving high redundancy that incur high investment, is of crucial importance for optimum operation of container movement [5]. Traditionally, the number of free-running equipments required is selected based on a crane/berth ratio. This ratio is predetermined by port consultants [6] at early port establishment as a function of the specific layout of the port. This ratio is non-sustainable as the port expands and cannot stand as a optimum equipment ratio at all time. There is an obvious lack of general empirical estimation to account for the current crane/berth ratio to execute optimum operation in the container transfer process.

In order to plan for equipments as well as port expansion, prior long term forecast of container throughput is an essential reference to gauge the throughput growth size .Monitoring

throughput changes of seasonal growth pattern aides planning activity involving the acquisition of additional equipment and even arrangement of the port's transportation system. However, permutation of transport system is not the focus point of this paper. This paper highlights the activity of equipment acquisition based on the forecasted throughput demand at the end of the long-term planning, also known as planning time horizon (PTH). There are a vast discipline of forecasting techniques that include time-series projection, simulation of one or more variables, input-output analysis and qualitative forecasting by expert opinion [7]. As of this paper, time-series projection is chosen as a forecasting tool for equipment planning – a total empirical approach.

In short, this paper has a twofold objective, first, to enhance the existing empirical formula for not only the number of quay crane needed but also to for other major equipments namely RTG and prime-movers. This follows the previous work on equipment estimation [2], [8], [9] with differing parameters and consideration to amend the existing algorithms. Second, to investigate the influence of different forecasting models [10], [11], [12] projecting the required number of equipments for optimum operation. The methodology adopted is to compare the significant difference of the enhanced empirical method to conventional equipment estimation methods from a set of sample data (undisclosed port name) by forecasting the future throughput from Holt-Winters method and seasonal ARIMA (0,1,1)(0,1,1)₁₂ – Box-Jenkins method. The results will be analyzed for accuracy and significant increase in numbers of equipment required at the end of the planning time horizon, set to be 5 years.

■2.0 LITERATURE REVIEW ON EQUIPMENT ESTIMATION APPROACH AND FORECASTING METHODS

2.1 UNCTAD and Other Empirical Models

One of the first reference for port expansion points to the UNCTAD model [13]. Equipment expansion is one of the four elements in UNCTAD development and expansion model, others being the container park area, container freight station and berth-day requirement. The determined number of container handled per crane, number of cranes per ship and moves are in function of per-berth requirement. UNCTAD model provides no empirical formula except but a simplistic graphical chart to estimate future demand support based on the four variables mentioned. However, it lacks control in terms of uncertainty and has a short range of parameter which cannot accommodate designs of larger terminal size. While others who followed after UNCTAD came up with various numerical models to analyze the handling capacity demands [7], [14], [15], [16], [17], [18], [47]. Loke (2012) equipment estimation formula is as below:

$$\Delta n_{i,pth} = \left(\frac{\Delta Q_{pth}}{MPH_i \cdot 24 \cdot ut_i \cdot 365} \right)$$

2.2 Costing Models

From the economical-feasibility stand-point, costing is also a basis of determination of equipment procurement size that became the focal point of researchers [19], [20]. Dekker's model for equipment expansion is based on a marginal approach that analyzes the need of expansion at intervals according to the current capacity of the terminal [8]. The basic approach is to calculate the optimal expansion by economical-order-purchase at steady-state-demand growth of each equipment [21]. Cost model

provides specific terminal equipment expansion with relative control in the financial costing of equipment procurement.

2.3 Queuing Theory

Queuing theory is a time definition of an entrance units queue in an immediate service of unloading or loading containers at the container berths and leave the system when the service has been performed [22]. Queuing theory holds on to the criteria that it is possible to accurately predict servicing time of ships rather than the estimated time of arrival of ships at terminal. Therefore, the objective is to ensure the handling capacity is equal or greater than the number of arriving ships, and so estimate the required number of port equipment. Consequently, queuing theory expressed itself in the form of berth occupancy rate ρ .

$$\rho = \lambda / \mu$$

Where, $\lambda = 1/\bar{t}_{arr}$, (\bar{t}_{arr} being the consecutive ship arrivals) and $\mu = 1/\bar{t}_{serv}$, (\bar{t}_{serv} being the reciprocal value of the service rate)

Based on parameters of consideration, the queuing problems are solved by iterating parameters of users preference such as probability of occupied berth, at service or unoccupied; average time of queue, time of service, number of ship queue, etc. Changes in values of terminal indexes and its impact on other parameters are largely computed by using Poisson's distribution. Advance simulation language based on queuing theories are such as PORTSIM [23], Modsim III [24], SIMPLE++ [25], ARENA and SLX [26], Visual SLAM [27], AweSim [28], etc.

Queuing theory not only models the required port parameters for sufficient support for optimum operation, it also provides a basic model for queuing cost which is of great interest optimize the service demand whilst not oversupplying equipment which leads to an uneconomical operation.

2.4 Conventional Way & Practices By Industry

By common practice, port authority's planning for equipment size is in accordance to a predetermined yard equipment to ship-to-shore crane designed by port consultant firms [6] in the early stage of the port development. This ratio is in function of the yard's physical layout, therefore, the ratio value differ for each distinct port due to their varying design of layout—parallel by RTG terminal or perpendicular by RMG terminal [29], and the demanded service rate. The assumption of this ratio estimation is that the horizontal transport capacity must be at least equal to the maximum quay handling capacity.

2.5 Forecasting Methods

Frankel [7] elaborates a series of forecasting methods in predicting container throughput demand that includes prospective economic over a time period of interest and other development such as the economical and social effect, specified port, modernization of existing port facilities, maintenance and investment implications.

In response to varying aspects of forecasting influence, forecasting projections are often done with the input of at least one input of data to multiple sources of input. Even so, forecasting can be classified into several approaches for example, model building and simulation, qualitative forecast and time series projection [7].

Historical data is the most reliable source of data to be interpreted for forecasting purposes. Models and simulation processes the data by techniques of trend extrapolation, pattern and probabilistic forecasting producing arrays of forecasts and decision tree matrices. Numerous algorithms and formulas developed are combined and adopt multivariate regression model [30] assumption to iterate the interrelationship between sets of variables. The relationship is then used to forecast the future throughput by fitting the characteristic observed by the model. An attribute theory, a new artificial intelligence [31], developed a fourfold attribute for throughput prediction. The influence of

GDP, cargo throughput, foreign trade and total import and export volume are amongst the relevant analysis with distinct pattern that when merged give a multi-spectrum of forecast of throughput which can be more reliable [32].

For qualitative forecasting, it deals with trades which are not susceptible to extrapolation and analysis or any methods that heavily builds on existing data. Expert surveys are main source of information to predicting future throughput with their rich experience as technologist, operators, planners and others.

Table 1 Previous researches scope on univariate forecasting for container throughput

Authors	Subject of Forecast	Model of Univariate Forecasting	Technique	Findings
Li, X. and Xu, S. (2011) [32]	Container Throughput - Shanghai Port	-Cubic exponential smoothing, -Grey Model, -Multiple regression analysis	Optimization by dual combined technique	Exponential smoothing and regression model prove better prediction
Xie, G., et al. (2013) [34]	Container Throughput - Hybrid Approach	- SARIMA model - X-12 ARIMA model - Classical Decomposition Model	Hybrid combination with "least squares support vector regression" model	Highlighting the importance of capturing seasonal and non-linearity for better forecasting
Chen, 2010 [35]	Container Throughput - Comparative Study	- Genetic Programming - ARIMA (X-11) - SARIMA	Comparison of few approaches	Suggesting Genetic Programming as optimum forecasting method
Chou, C.-C., et al. (2008) [36]	Container Throughput - Taiwan Port	- Regression model	Generate a new modified regression model	Results proposed modified regression model for higher prediction accuracy
Seabrooke, W., et al. (2003) [37]	Container Throughput - Hong Kong Port	- Conventional Regression model	Forecasting with other affecting factors.	Results yield more reliable pattern of throughput growth
Peng, W.-Y. and C.-W. Chu (2009) [38]	Container Throughput - Comparative Study	- Decomposition - Trigonometric regression - Regression with seasonal dummy - Hybrid grey model, - Sarima model	By applying monthly data input and evaluation of error profile	classical decomposition model appears to be the best model for forecasting container throughput with seasonal variations.
Gosasang, V., et al. (2011) [39]	Container Throughput - Comparative Study	- Neural Network - Linear Regression	By measurement of RMSE, MAE	Neural Network as being the best application for forecasting
DuanXueyan, XuGuanglin, Yu Siqin (2012) [31]	Container Throughput - Application Study	Attribute Theory (artificial intelligence forecasting)	By applying mapping theory and conversion degree function	Attribute theory is effective and feasible with comprehensive consideration of influencing factors

Delphi method [33] is one of the popular approach by well-defining questionnaires to specific parties that yields a consensus of factors and opinions on future container throughput.

In the spectrum of time-series forecast, also called the univariate forecasting model, is particularly useful when little is known about the underlying revolution of the history of container throughput pattern. From a simple linear regression extrapolation to neural network analysis [40], time-series forecasting models has become complex and detail in finding the most fitting function to the real variable in order to forecast according from past trends and pattern. Researchers today developed better forecasting models by comparing with other models through varies application and techniques like ACF, PACF, MAPE, etc. Table 1 shows the recent researches and its findings of superior performing models for specific applications.

The basic forecasting approach are mostly regression-based and highlights the importance of placing weightage on seasonal pattern consideration and the analysis of error (RMSE, MAE, MAPE).

2.6 Holts-Winter's Exponential Smoothing

Some of the most successful forecasting methods are based on the concept of exponential smoothing. Exponential smoothing techniques are simple tools for smoothing and forecasting a time series that is, a sequence of measurements of a variable observed at equidistant points in time. Smoothing time series aims at eliminating the irrelevant noise and extracting the general path followed by the series. The first exponential smoothing originated from the work in the US Navy in 1944, Robert G. Brown developed the algorithm when tracking the velocity ad angle used in firing at submarines as a research analyst. He further developed it in 1950s to discrete time series handling trend and seasonality [10]. Later Charles Holts in the US office of the Naval Research, developed a different smoothing trend and seasonal component with the novelty of incorporating the additive ad multiplicative component [11]. Soon, his student Peter Winters [42] provided empirical test on Holts method and, therefore, the seasonal version of Holt's method is called Holt-Winters' method.

There are two variations to this method which differ in the seasonal component. The additive method is preferred when the seasonal variations are roughly constant through the series, while

the multiplicative method is preferred when the seasonal variations are changing proportional to the level of the series [43].

2.7 Seasonal ARIMA (SARIMA)

The AutoRegressive Integrated Moving-Average (ARIMA) procedure analyzes and forecasts equally spaced univariate time series data, transfer function data, and intervention data. This univariate time series model was first popularized by George Box and GwilymMeirion Jenkins, frequently called “Box–Jenkins models” because it [12] proposed a complete methodology for modeling time series which consists of three phases: identification, estimation and testing, and application. It is suitable for use with a stationary time series. However, ARIMA and SARIMA are built on linear assumptions and they cannot capture the nonlinear patterns hidden in the original data, which leads to poor forecasting performance [41].

3.0 METHODOLOGY

This section explains the framework of calculating and comparing the outcome from forecast data derived from the Holts-Winter and SARIMA method. The empirical method of calculation is tabled against the conventional equipment ratio estimation, whilst the actual planning figures from port data will be compared. The empirical calculation is done by adopting the parameters like equipment capacity, coefficient and handling rates [6], [7], [39] and equipment profiles. Equipment ratio estimation is simply taken from planning practice figures to extrapolate equipment size by number of projected throughput. Figure 1 below is a general flow-chart describing the framework.

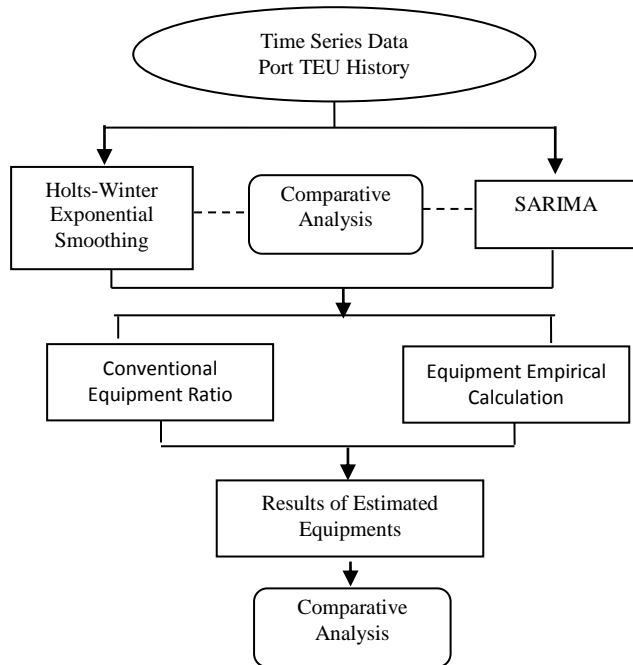


Figure 1 The overall process of the comparative forecasting model for equipment estimation

3.1 Equipment Estimation

The equipment planning time frame selected here is 5 years, which is a common practice in port expansion. T_t represents the

total number of years, that is set as planning time horizon as below:

$$T_t = (T_{pth})$$

$$T_{pth} = 5 \text{ years}$$

To match the capacity of the various equipments in support of the increased throughput, the following equation determines the additional number of equipments need for the new expansion phase.

$$\Delta n_{i,j} = n_{i,j} - n_{i,j-1} \quad \text{---(1)}$$

$\Delta n_i, n_{i,j}, n_{i,j-1}$ represents the additional equipment needed, number of equipment needed at expansion, number of equipment available since previous expansion. Function i is numbered by 1,2,3 as 1= qc (quay crane); 2 = rtg (rubber-tire gantry); 3 = pm (prime-mover); j represents the expansion year phase ($j = 1, 2, 3, \dots, pth$). To derive the number of equipments need for the entire planning time horizon (pth), the equation (1) is adjusted by setting in the planning time phase and the initial available number of equipments.

$$\Delta n_{i,pth} = n_{i,pth} - n_{i,0} \quad \text{---(2)}$$

Point of interest after forecasting the throughput is the number of equipment, which is calculated empirically by the following equation (UNCTAD, 1976; Loke et al., 2004). The basic algorithm by Loke is enhanced by including additional factors from earlier reference, TEU factor, handling ratio, maintenance period and the breakdown of equipments move per hour (Equation 3) is added.

$$n_{i,pth} = \left(\frac{Q_{pth}}{f \cdot MPH_i \cdot ts \cdot r \cdot ut_i \cdot 365} \right) \times \left(\frac{1}{1 - mdt_i} \right) \quad \text{---(3)}$$

$$\Delta n_{i,pth} = \frac{Q_{pth}}{f \cdot MPH_i \cdot ts \cdot r \cdot ut_i \cdot 365 \cdot (1 - mdt_i)} - n_{i,0} \quad \text{---(4)}$$

- $n_{i,pth}$ =total number of equipment i , at the end of planning time horizon
- $n_{i,0}$ = number for addition equipment i at initial planning phase $t=0$
- $\Delta n_{i,pth}$ = number for addition equipment i , at planning time horizon from planning time, $t=5$
- Q_{pth} = throughput amount at the end of planning time horizon (TEU)
- f =TEU factor
- MPH_i = Moves per hour for equipment i (move/hr)
- T_s = time of service of berth (hr/day)
- nb = number of berth
- r_i = time handling ratio for equipment i (%)
- ut_i = utilization rate of equipment,
- mdt = maintenance & breakdown time (%)

$$MPH_i = \frac{3600s}{\frac{d_i}{v_i} + tD_i + tT_i} \quad \text{---(5)}$$

- d_i = average distance traveled per move of equipment i
- v_i = velocity of equipment i
- tD_i = time delayed
- tT_i = time of transfer

3.2 Additive Holt-Winters Model

The "h-step ahead forecast" for the multiplicative Holts-Winter's equation is a combination of an estimate of trend level (ℓ_t), growth rate (b_t) and seasonal factor (sn_t) as below:

$$\hat{Q}_{t+h} = \ell_t + hb_t + sn_{t+h-L} \quad (h = 1,2,3,\dots) \quad --(6)$$

Each estimate factor formula of ℓ_t , b_t and sn_t can be expressed as

$$\ell_t = \alpha(y_{ct} - sn_{t-L}) + (1-\alpha)(\ell_{t-1} + b_{t-1}) \quad --(7)$$

$$b_t = \gamma(\ell_t - \ell_{t-1}) + (1-\gamma)b_{t-1} \quad --(8)$$

$$sn_t = \delta(y_t - \ell_t) + (1-\delta)sn_{t-L} \quad --(9)$$

Where α , and γ are smoothing constants between $0.02 < \alpha, \beta, \gamma < 0.9$. And L is the number of seasons (e.g. L=4, for quarterly data). (reference for constant range)

3.3 Seasonal ARIMA Model

Example of an ARIMA(1,1,1)(1,1,1)_s model (without a constant) for s-lag data and can be written as:

$$\left(1 - \sum_{i=1}^p \theta_i B^i\right) \cdot \left(1 - \sum_{i=1}^q \phi_i B^i\right) \cdot (1-B)^d \cdot (1-B^s)^p y_t = \left(1 - \sum_{i=1}^a \theta_i B^i\right) \left(1 - \sum_{i=1}^q \phi_i B^i\right) a_t$$

↑ (Non-seasonal AR(1))
↑ (Non-seasonal difference)
↑ (Non-seasonal MA(1))
↑ (Non-seasonal MA(1))

↑ (Seasonal AR(1))
↑ (Seasonal difference)
↑ (Seasonal MA(1))

--(10)

Basic steps to fitting ARIMA model to the forecast data can be divided into a simple 5-step-procedure. First, plot the data accordingly to its axis which may reveal some features that indicates the pattern of seasonal and stationary. Second, choose to transform the data by performing the natural logarithm function to minimize the standard deviation. Then, the crucial step of identifying the order (p,d,q) and (P,D,Q), if seasonal ARIMA is used, must be done with care. The data plot may aide in identifying the differencing order, d (beware of overdifferencing). While inspection of the autocorrelation (ACF) and partial autocorrelation function can help identify the AR order and MA order. Fourth, estimation for the model parameter can be performed using Yule-Walker equation or any time series software such as SAS, Minitab and Statistica. However, the maximum likelihood and method of least squares must be observed. Lastly, the residual diagnosis must be done by reviewing non-residuals' ACF and PACF, histogram that indicate Gaussian white noise, else iteration has to be done by estimating another set of orders (p,d,q).

Since the "ARIMA (0,1,1)(0,1,1)₁₂" is used, which denotes a zero order autocorrelation, 1st order difference, 1st order moving average, zero order seasonal autocorrelation, 1st order seasonal difference, 1st order seasonal moving average. The seasonal analysis period is 12, which is a monthly interval in a year's period. Therefore, ARIMA(0,1,1)x(0,1,1)₁₂ can be expressed as:

$$(1-B)^1 \cdot (1-B^{12})^1 y_t = (1 - \theta_1 B^1 - \Theta_1 B^{12} + \theta_1 \Theta_1 B^{13}) a_t \quad --(11)$$

Where, B, B12, B13 are coefficients of the ARIMA model (0,1,1)(0,1,1)₁₂.

3.4 Accuracy Model Diagnostics

The issue of measuring the accuracy of forecasts from different methods has been central of attention. Error is described in a similar fashion as forecasting by one-step ahead forecast error, which is simply $e_t = Y_t - \hat{Y}_t$, regardless of how the forecast was produced. Therefore, the forecast h-step-ahead forecast error is $e_{t+h} = Y_{t+h} - \hat{Y}_{t+h}$.

Common practice uses the basic scale-dependent measures are based on absolute error or squared errors. Comparing mean absolute error (MAE) and mean squared error (MAE), it is easier to understand and compute the accuracy on the same scale. On the other hand, percentage error have advantage of being scale independent and is frequently used to compare performance between different data sets. Below are the empirical expression of the errors:

Mean Square Error

$$MSE = \frac{1}{n} \sum_{t=1}^n (y_t - \hat{y}_t)^2 \quad ---(12)$$

Mean Absolute Error

$$MAE = \frac{1}{n} \sum_{t=1}^n (y_t - \hat{y}_t) \quad ---(13)$$

Mean Percentage Error

$$MPE = \frac{1}{n} \sum_{t=1}^n \left(\frac{y_t - \hat{y}_t}{y_t} \right) x 100 \quad ---(14)$$

Mean Absolute Percentage Error

$$MAPE = \frac{1}{n} \sum_{t=1}^n \left(\frac{|y_t - \hat{y}_t|}{y_t} \right) x 100 \quad ---(15)$$

However, the most favored measure is the Mean Absolute Percentage Error (MAPE) proposed by Makridakis (1993) [44].

4.0 RESULTS

4.1 Holts-Winter Result

Parameter grid search is performed by iterating for the least error for the parameter chosen for the set of data. The above Table 2 shows that at 406th iteration, the mean absolute error(MAE), sum of squared error (SSE), mean squared error (MSE) are the least with other error indicators at relative low, hence, the parameter alpha, delta and gamma is chosen. Then, Holts-Winter method is performed using "Minitab".

Table 2 Iteration of parameter

Parameter grid search (Smallest abs. errors are highlighted) (Spreadsheet1.sta)									
Model: Expon. trend, add. season (12); S0=208E3 T0=1.004									
VAR7									
Model Number	Alpha	Delta	Gamma	Mean Error	Mean Abs Error	Sums of Squares	Mean Squares	Mean % Error	Mean Abs % Error
406	0.600000	0.100000	0.100000	-1316.07	25638.17	2.465145E+11	1.208404E+09	-0.387033	5.762378
325	0.500000	0.100000	0.100000	-1286.40	26226.43	2.482998E+11	1.217156E+09	-0.375158	5.893909
487	0.700000	0.100000	0.100000	-1384.04	25736.29	2.517456E+11	1.234047E+09	-0.409643	5.750547
244	0.400000	0.100000	0.100000	-1310.60	27021.79	2.569530E+11	1.259574E+09	-0.378398	6.077951
415	0.600000	0.200000	0.100000	-1322.62	26259.37	2.601814E+11	1.275399E+09	-0.396447	5.827126
407	0.600000	0.100000	0.200000	-1381.83	26599.75	2.616455E+11	1.282576E+09	-0.429059	5.999477
496	0.700000	0.200000	0.100000	-1404.52	26060.50	2.619092E+11	1.283869E+09	-0.414759	5.779621
568	0.800000	0.100000	0.100000	-1495.18	26319.68	2.636571E+11	1.292437E+09	-0.440967	5.833136
334	0.500000	0.200000	0.100000	-1258.63	27041.47	2.644052E+11	1.296104E+09	-0.391418	5.980221
326	0.500000	0.100000	0.200000	-1351.13	27201.25	2.656962E+11	1.302432E+09	-0.415350	6.158452

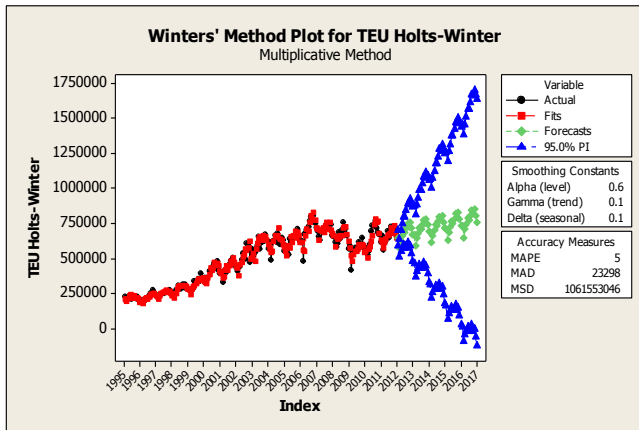


Figure 2 TEU throughput of Holt-Winters forecast

The forecast (Figure 2) predicts a strong increase of throughput in the coming years, based on unknown external factors but only based on the information from the data set.

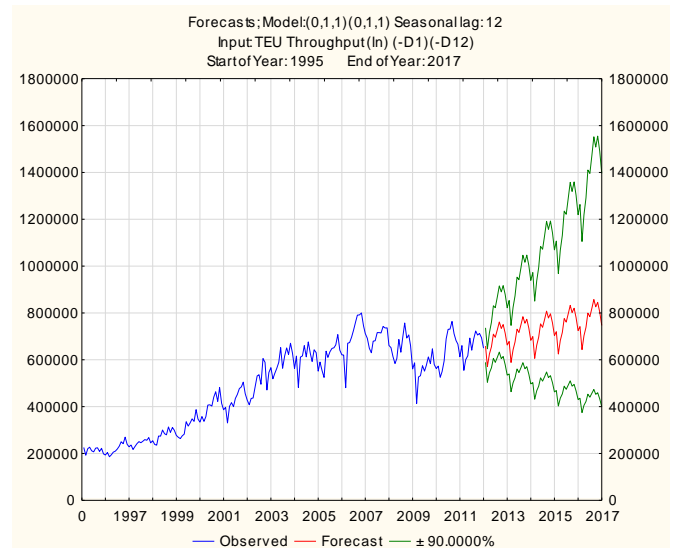


Figure 4 TEU throughput of SARIMA forecast

Result (Figure 4) also shows a steady increasing pattern for the TEU throughput forecast for 2012 to 2016. Below, Table 3 shows the parameter for seasonal and non-seasonal moving average coefficient, also the indication of errors ensuring best fit of model.

Table 3 Parameter iteration results of least error

Input: TEU Throughput						
Transformations: ln(x),D(1),D(12)						
Model:(0,1,1)(0,1,1) Seasonal lag: 12 MS Residual= .00458						
Paramet.	Param.	Asympt. Std. Err.	Asympt. t (189)	p	Lower 95% Conf	Upper 95% Conf
q(1)	0.504017	0.052674	9.56861	0.000000	0.400112	0.607921
Qs(1)	0.802000	0.042049	19.07306	0.000000	0.719054	0.884945

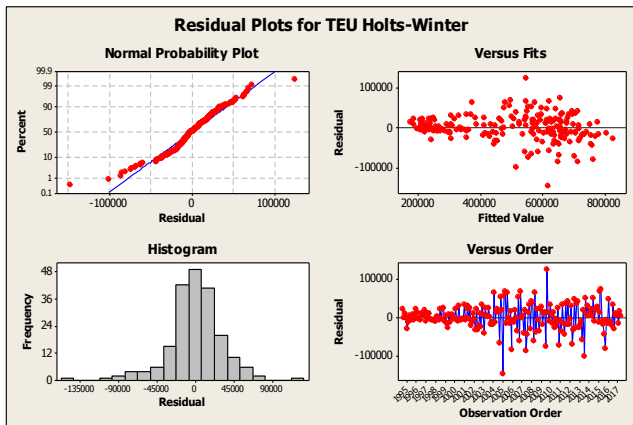


Figure 3 Normal probability, histogram and goodness of fit of results residual

The probability plot and histogram of residual-frequent (Figure 3) indicates a healthy set of skewed and normally distributed pattern for the set of data. The residuals versus fits graph indicates nonconstant variance which spreads unevenly across the fitted values. Residual versus order also fluctuates around zero except the middle -end section fans, which is still acceptable.

4.2 Seasonal ARIMA (0,1,1)(0,1,1)₁₂

Data is analyzed by checking autocorrelation (ACF) and partial autocorrelation (PACF) before carrying out ARIMA order assignment. After analysis, function of natural logarithm and difference in lag 1 and lag12 is required to ensure desirable ACF and PACF pattern. Then, SARIMA (0,1,1)(0,1,1) model is performed using "Statistica".

Following are the probability plot and histogram of residual-frequent (Figure 5, 6 & 7) which indicate a healthy set of skewed and normally distributed pattern for the set of data. ACF and PACF of the data residual (Figure 8 & 9) are also shown, indicating acceptable trend, with only one spike at lag 3 for both functions.

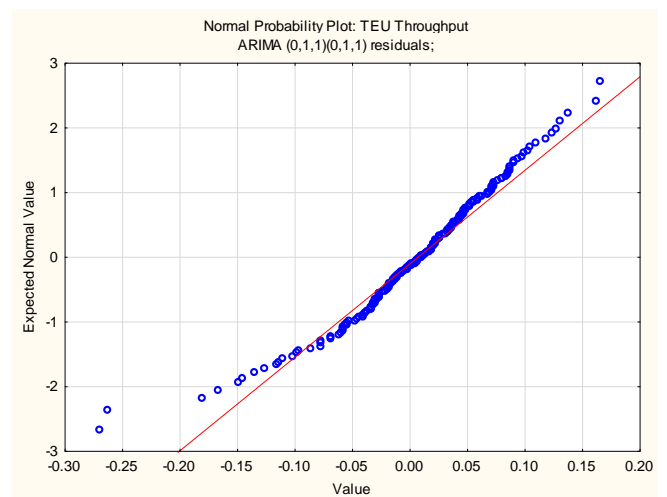


Figure 5 Normal probability plot of SARIMA residual

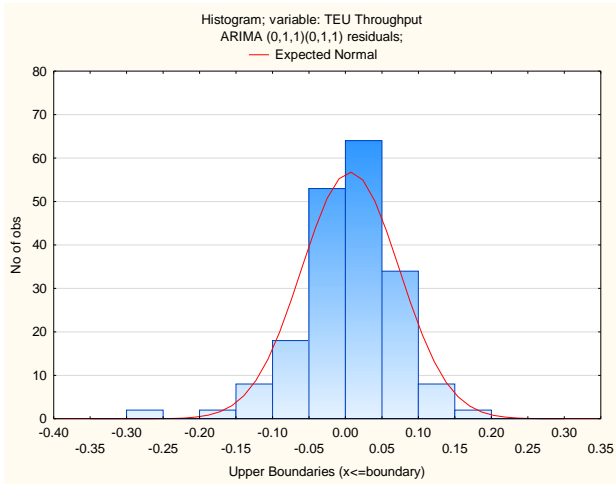


Figure 6 Histogram of SARIMA residual

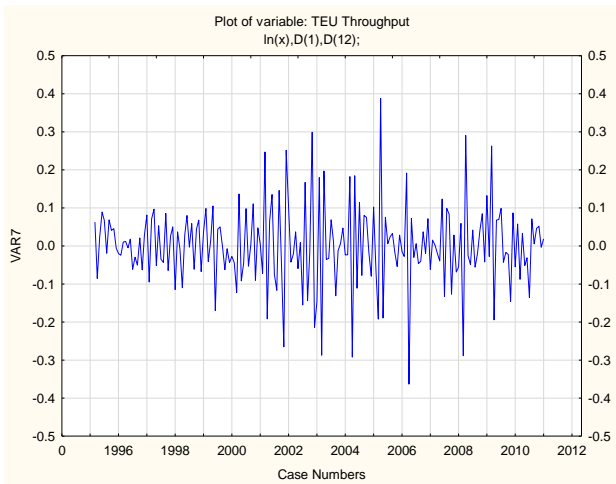


Figure 7 SARIMA residual plot

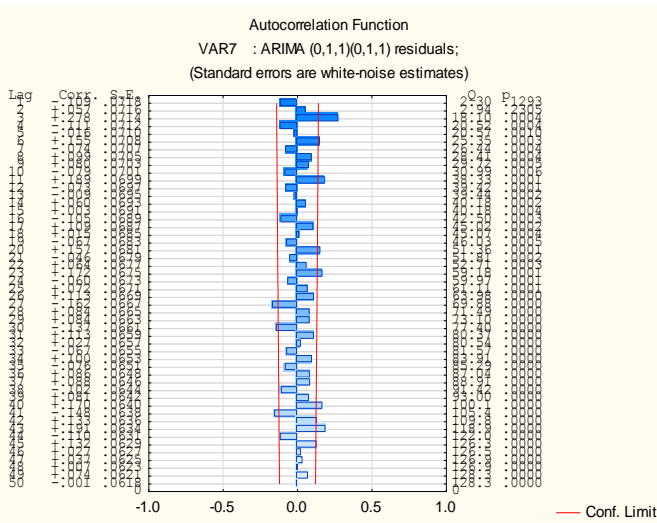


Figure 8 Autocorrelation function for residual

pattern of forecasting by both models having only slight difference in the maximum throughput forecast in August (Table 4). The maximum throughput will be the targeted service throughput for the fulfillment of equipment capacity.

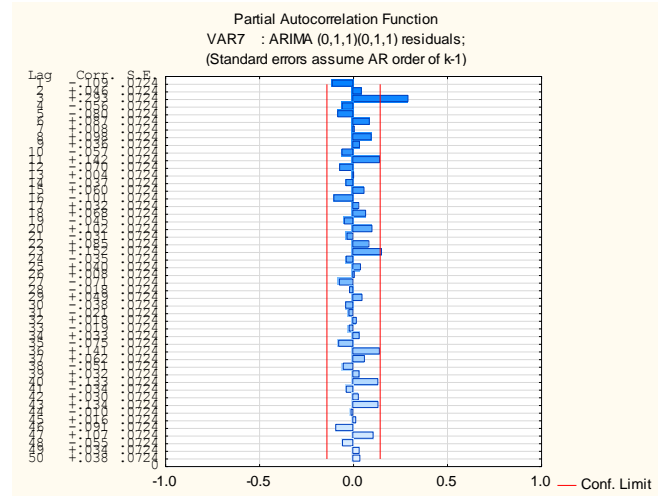


Figure 9 Partial autocorrelation function for residual

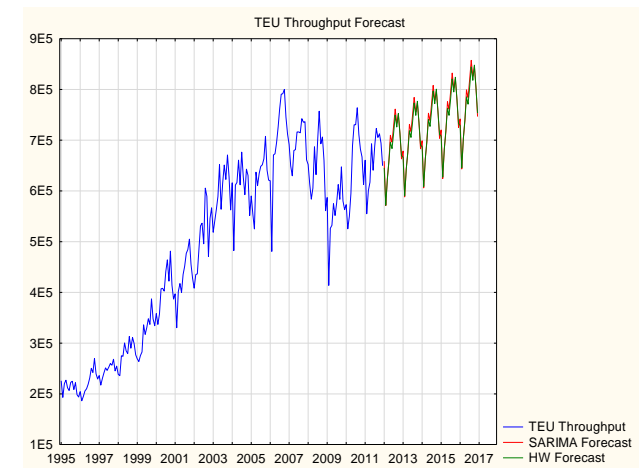


Figure 10 Comparative TEU throughput forecast (HW vs SARIMA)

Table 4 TEU Forecast at Planning Time Horizon (2016)

Time	SARIMA Forecast	Holt-Winters Forecast
Jan-16	729111	741943
Feb-16	645650	643221
Mar-16	703509	703077
Apr-16	740580	738655
May-16	785465	799407
Jun-16	770994	784006
Jul-16	804231	819898
Aug-16	844711	857469
Sep-16	818067	826333
Oct-16	848105	845243
Nov-16	803020	803711
Dec-16	753527	746766

For comparative Analysis of Holt-Winters and SARIMA Forecast, both forecast are plotted on the same chart (Figure 10) for seasonal trend observation. The results shows a closely fitted

4.3 Results of Empirical and 'Ratio' Method for Equipment Estimation

Table 5 Estimation of equipment planning

Method/Time Series Model	STS Crane	RTG	Prime Mover
2011 (Actual)	74	97	933
2011 (Empirical)	69	153	306
Empirical – HW (2016-PTH Forecast)	80	179	358
Empirical – SARIMA (2016-PTH Forecast)	81	181	363
Ratio – HW (2016-PTH Forecast)	80	160	400
Ratio – SARIMA (2016-PTH Forecast)	81	162	405

Using the formulas and information on the equipment-crane ratio, the numbers of required equipment estimation at planning time horizon is tabulated in Table 5.

5.0 DISCUSSION

Though both the forecasting model proofed to be giving close similarity in results, we note the superiority of the SARIMA model for its flexibility of transforming and eliminating spikes in ACF and PACF analysis. Since the set of TEU throughput history data is a steady increase, both the forecasting model is considered as having same prediction capability, though differing in concept.

Noting that the actual number of RTG and prime mover far exceeds the empirical method, the factor in play here is the equipment dynamics adopted by the specific port. The green and sustainable trend of [45] equipment combination are mainly STS crane with the support of RTGs and Prime Mover, which produce lesser CO₂ emission as compared to those which substitute RTGs for forklifts, side-loaders, reachstackers, etc. Substituting 56 RTGs, the unnamed port compensated with 10 rail-mounted gantries (RMG), 127 forklifts, 147 top-stackers and 37 side-stackers. However, possible varying consideration of parameter assumption [46] has slight influence over the estimation of equipment, nonetheless, the major reference for equipment planning is the requirement of the STS crane.

The empirical method for equipment estimation has provided a means to account for the conventionally ratio-determined equipment profile. The 'check and balance' shows only a small acceptable margin difference. Results also prove that the use of more RTG can reduce the use of smaller equipment such as forklifts, stackers and prime-mover, which are major contributors of environmental waster. With the technology of electrification of RTG should all the more drive port authorities to the use of 'state-of-the-art' technology for environmental purposes.

Since the TEU throughput forecast yields only a small margin of 12758 TEU difference, the effect on equipment empirical estimation has but little influence with differing 1 STS crane; 2 RTGs and 5 prime movers. At planning time horizon, the ratio method of estimation yields about 10% less in deviation from the empirical method. Hence, empirical method may provide for redundancy that could be utilized in case of massive equipment breakdown.

Since, the specific port has huge amount of prime-movers, the planning ahead is to merely procure RTGs, or even eRTGs (fully-electric or hybrid) to facilitate operation whilst slowly scrapping small equipments such as forklifts and top-stacker, etc as they wear off. Not only will this reduce environmental waste but also greatly reduce the operators of the many equipments reduced.

6.0 CONCLUSION

Though Holt-Winter and SARIMA (0,1,1)(0,1,1)₁₂ methods yield close results of forecasting, they are still univariate methods only considering trends in the data set assuming no known factors influencing it. Future equipment estimation should incorporate multivariate models evaluating factors such as GDP, import-export trend, population growth, immigration, inflation, etc [32].

For future consideration of equipment planning, it will be interesting to incorporate a green and sustainable planning system to perform equipment profile estimation with integration with other elements of the port planning such as its hinterland, container park area, container freight area, berthing zone and other terminal area, etc [13].

Last but not least, an in-depth investigation on yard layout area and equipment profile dynamics and operation parameters should be evaluated properly or even a standard value for specific type of port should be proposed. The effects on equipment costing will be significant and will be of great concern to stakeholders in the planning process.

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References

- [1] Steenken D., S. Vob, R. Stahlbock. 2004. Container Terminal Operation and Operations Research: A Classification and Literature Review. *Spectrum*. 26: 3–49.
- [2] Young-Tae Chang, Jose Tongzon, Meifeng Luo & Paul Tae-Woo Lee. 2012. Estimation of Optimal Handling Capacity of a Container Port: An Economic Approach. *Transport Reviews. A Transnational Transdisciplinary Journal*. 32(2): 241–258. DOI: 10.1080/01441647.2011.644346
- [3] Prakash Gaur. 2005. Port Planning as a Strategic Tool: A Typology, Master Thesis of Science in Transport and Maritime Economics. Institute of Transport and Maritime Management Antwerp University of Antwerp.
- [4] Jasmine, L. S. L., Eddy, V. D. V. 2012. Green Port Strategy for Sustainable Growth and Development. Nanyang Technological University & University of Antwerp, Unknown Publisher.
- [5] Joan C. Rijsenbrij, Armin Wieschemann. 2011. Sustainable Container Terminals: A Design Approach. *Handbook of Terminal Planning, Operations Research/Computer Science Interfaces Series*. 49: 61–82.
- [6] Nima Sharif Mohseni. 2011. Master Thesis Project: Developing a Tool for Designing a Container Terminal Yard, Delft University of Technology & Royal Haskoning.
- [7] Frankel, E. G. 1987. *Port Planning and Development*. Wiley-Interscience Publication. ISBN 0-471-83708-3.
- [8] Loke, K. B., Kader, A. S. A. and Zamani, M. 2012. Optimising Expansion Control On Quay Crane Development In Container Terminal, International Conference on Marine Technology Kuala Terengganu, Malaysia, 20-22 October 2012, UMT/FMSM/MARTEC/MMP-17.
- [9] MOMAF. 1998. Optimal Port Capacity Study on National Ports (Contract Research Report Written in Korean) (Seoul: The Korea Maritime Institute).
- [10] Brown, R. G. 1963. *Smoothing, Forecasting and Prediction of Discrete Time Series*. Prentice Hall, Englewood Cliffs, New Jersey

- [11] Holt, C. C. 2004. Forecasting Seasonals and Trends by Exponentially Weighted Moving Averages. *International Journal of Forecasting*. 20: 5–10.
- [12] Box, G. E. P., & Jenkins, G. M. 1976. *Time Series Analysis: Forecasting and Control*. Hoboken USA: John Wiley & son, Inc.
- [13] UNCTAD. 1985. Port Development—A Handbook for Planners in Developing Countries. United Nations, New York. 227.
- [14] Kuroda, K., Takebayashi, M., Tsuji, T. and Muto, M. 1999. Influence of Port Management Policy on the Behavior of Container Liner Ship Company and Shippers. *Journal of EASTS*. 3(2): 127–138.
- [15] Chu, C. Y. and W. C. Huang. 2005. Determining Container Terminal Capacity on the Basis of an Adopted Yard Handling System. *Transport Reviews*. 25(2): 181–199.
- [16] Dally, H. K. 1983. *Container Handling and Transport—A Manual of Current Practice*. London: Cargo Systems IIR Publications Ltd.
- [17] Dharmalingam, K. 1987. Design of Storage Facilities for Containers—A Case Study of Port Louis Harbour, Mauritius, Ports and Harbors, September. 27–31.
- [18] Itsuro, W. 2001. *Container Terminal Planning—A Theoretical Approach*. Leatherhead, UK: World Cargo Publishing.
- [19] Dekker Sander & Verhaeghe, R. J. 2008. Development of a Strategy for Port Expansion: An Optimal Control Approach. *Maritime Economic and Logistics*. 10: 258–274.
- [20] Saman Kader. 1997. Cost Modelling for Inland Waterway Transport Systems. Doctor of Philosophy in Marine Engineering. Liverpool John Moores University. 276.
- [21] Silver, E., D. Pyke, and R. Peterson, 1998. *Inventory Management and Production Planning and Scheduling*. Wiley, USA.
- [22] Zdenka Zenerović, Edna Mrnjavac (Unknown). Modelling of Port Container Terminal Using The Queuing Theory. Dept. of Maritime Studies, University of Rijeka.
- [23] Nevins, M. R., Macal, C. M., Love, R. J. and Bragen, M. J. 1998. Simulation, Animation, and Visualization of Seaport Operations. *Simulation*. 71(2): 96–106.
- [24] Gambardella, L. M., Rizzoli, A. E. and Zaffalon, M. 1998. Simulation and Planning of Intermodal Container Terminal. *Simulation*. 71(2): 107–116.
- [25] Yun, W. Y. and Choi, Y. S. 1999. A Simulation Model for Container-Terminal Operation Analysis Using an Object Oriented Approach. *International Journal of Production Economics*. 59(1–3): 221–230.
- [26] Tahar, R. M. and Hussain, K. 2000. Simulation and Analysis for the Kelang Container Terminal operations. *Logistics Information Management*. 13(1): 14–20.
- [27] Legato, P. and Mazza, R. M. 2001. Berth Planning and Resources Optimization at a Container Terminal via Discrete Event Simulation. *European Journal of Operational Research*. 133(3): 537–547.
- [28] Nam, K.-C., Kwak, K.-S. and Yu, M.-S. 2002. Simulation Study of Container Terminal Performance. *Journal of Waterway, Port, Coastal, and Ocean Engineering*. 128(3): 126–132.
- [29] Rijsenbrij, J. and A. Wieschemann. 2011. Sustainable Container Terminals: A Design Approach. Handbook of Terminal Planning. J. W. Böse, Springer New York. 49: 61–82.
- [30] Chatterjee, S. and A. S. Hadi. 2012. *Regression Analysis by Example*. 5th ed. New York: John Wiley & Sons.
- [31] Duan X. et al. 2012. Application of Attribute Theory for Container Throughput Forecast. IEEE International Conference on Granular Computing 2012. DOI: 978-1-4673-2311.
- [32] Li, X. and Xu, S. 2011. A Study on Port Container Throughput Prediction Based on Optimal Combined Forecasting Model in Shanghai Port. ICCTP 2011. 3894–3905.
- [33] Rowe, G. 2007. A Guide to Delphi. *Foresight: The International Journal of Applied Forecasting*. 8: 11–16.
- [34] Xie, G. et al. 2013. Hybrid Approaches based on LSSVR Model for Container Throughput Forecasting: A Comparative Study. *Applied Soft Computing*. 13(5): 2232–2241.
- [35] Chen, S.-H. and J.-N. Chen. 2010. Forecasting Container Throughputs at Ports Using Genetic Programming. *Expert Systems with Applications*. 37(3): 2054–2058.
- [36] Chou, C.-C., et al. 2008. A Modified Regression Model for Forecasting the Volumes of Taiwan's Import Containers. *Mathematical and Computer Modelling*. 47(9–10): 797–807.
- [37] Seabrooke, W. et al. 2003. Forecasting Cargo Growth and Regional Role of the Port of Hong Kong. *Cities*. 20(1): 51–64.
- [38] Peng, W.-Y. and C.-W. Chu. 2009. A Comparison of Univariate Methods for Forecasting Container Throughput Volumes. *Mathematical and Computer Modelling*. 50(7–8): 1045–1057.
- [39] Gosasang, V. et al. 2011. A Comparison of Traditional and Neural Networks Forecasting Techniques for Container Throughput at Bangkok Port. *The Asian Journal of Shipping and Logistics*. 27(3): 463–482.
- [40] Liu, C.-I., et al. 2004. Automated Guided Vehicle System for Two Container Yard Layouts. *Transportation Research Part C: Emerging Technologies*. 12(5): 349–368.
- [41] Gosasang Veerachai, Watcharavee Chandraprakaikul, Supaporn Kiattisins. 2010. An Application of Neural Networks for Forecasting Container Throughput at Bangkok Port, Proceedings of the World Congress on Engineering 2010 Vol I, WCE 2010, June 30 - July 2, 2010, London, U.K.
- [42] Winters, P. R. 1960. Forecasting Sales by Exponentially Weighted Moving Averages. *Management Science*. 6: 324–342.
- [43] Roland Fried, Ann Cathrice George. 2011. Exponential and Holt-Winters Smoothing. International Encyclopedia of Statistical Science. DOI 10.1007/978-3-642-04898-2, Springer-Verlag Berlin Heidelberg.
- [44] Makridakis, S., C. Chatfield, M. Hibon, M. Lawrence, T. Mills, K. Ord & L. F. Simmons. 1993. The M2-competition: A real-time judgmentally based forecasting study. *International Journal of Forecasting*. 9: 5–22.
- [45] Sander Dekker. 2010. Sustainable Port Development In The Netherlands—Framework for a Comprehensive Approach Applied To Amsterdam Port. 12th Wctr Lisbon, Portugal. Strategic Consultant Transport & Economics, Grontmij Nederland Bv.
- [46] Park Nam-Kyu, Branislav Dragović. 2009. A Study of Container Terminal Planning, Faculty of Mechanical Engineering, Belgrade. *FME Transactions*. 37: 203–209.
- [47] Zamani Ahmad. 2006. The Application of Fuzzy Expert System to Preliminary Development Planning of Medium Size Container Terminal. Doctor of Engineering in Engineering Business Management. Universiti Teknologi Malaysia. 355.