

DEPARTMENT OF TRANSPORT AND REGIONAL ECONOMICS

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Short-term Forecasts of Container Throughput
in the Port of Antwerp**

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A Univariate Analysis: Short-term Forecasts of Container Throughput in the Port of Antwerp

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Abstract

The relation between transportation and economic activity is complex and interrelated. From this complexity arises the difficulty of forecasting the port throughput, which plays an essential part in planning the port operations, not only for the port stakeholders but also for the development of hinterland activities and connectivity network. The aim of the univariate method used in this paper is to estimate short-term forecasting and to provide initial insight of the stochastic process for further research in the multiple regression analyses. The SARIMA model is found to be quite appropriate for the container throughput since seasonality exists in the time series. The advantage of the univariate method is that it is independent of other variables, provide a generic and a simple model that can be updated frequently and the model can be applied to other ports.

Keywords: Container throughput; Univariate analysis; ARIMA; Forecasting; Seasonality.

1 INTRODUCTION

Ports as an economic unit provide socio-economic opportunities and benefits within the surrounding territory and the regional level. On the one hand, it has a direct effect, as it generates employment and business earnings during the port construction and operation. On the other hand there are indirect effects such as facilitation of trade, employment in port supporting sectors, attraction of companies active in the port and maritime sector as well of companies for which the vicinity of a port is important. Port investments are expected to act as a catalyst in the regional economic development constrained by the optimal utilisation of the infrastructure and ideal capacity. In the seminal work of Jansson and Shneerson (1982), ports are considered as public utilities and their objective is not only to maximise profit but mainly to create social net benefit.

The Port of Antwerp is located centrally within the Hamburg-Le Havre range, it is one of the main top European hub ports, and it has the capacity to handle 15 million TEUs (twenty-foot equivalent units) per year. The Port of Antwerp is Europe's second largest by total volume in tonnes in 2011 (Antwerp, August 2012). In 2010, the Port of Antwerp share of direct and total value added in Belgian GDP was 2.8% and 5.4% respectively and employment represented 1.5% (direct) and 3.7% (total) of Belgian employment (Mathys, July 2012). In 2012, the port handled 8.63 million TEUs making it the third largest port in terms of

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TEUs in Europe ¹. It is important for the competitive position of the port and the port operators that the huge volumes of containers can be handled in a smooth and efficient way not only at the terminals, but also on the connections with the hinterland. Especially for the planning of the operations, short term forecasts are important.

The advantage of the univariate procedure applied in the paper, is that it offers a systematic approach to building, analysing, and forecasting time series models. The use of a univariate analysis is justified by the availability of long series of high frequency data, and the independency of other variables that are needed in causal methods. The objective for using the univariate analysis is to capture the short-term variations represented by the monthly data, to forecast and to have an initial insight regarding the future evolution of cargo volume in ports.

In Wen-Yi and Ching-Wu (2009), six univariate models to forecast the container throughput volume are compared for three major ports in Taiwan, concluding that the classical decomposition method and seasonal autoregressive moving average model (SARIMA) give the best forecast, depending on the forecasting accuracy criterion adopted.

In this paper univariate models are used to forecast container throughput in the port of Antwerp. Special interest goes to the modelling of the seasonal effects by using a SARIMA model.

The next section presents the methodological framework of the autoregressive integrated moving average (ARIMA) model and seasonal autoregressive integrated moving average (SARIMA) model. The empirical results and analysis of the container throughput in the Port of Antwerp are presented in section 3. Finally in section 4, the conclusions and the main findings are drawn and developments for further research are mentioned.

2 METHODOLOGY

The basic idea of a univariate time series model is that the value of variable Y_t , can be considered as a combination of its own history - *Autoregressive (AR)* ($Y_{t-1}, Y_{t-2}, \dots, Y_{t-p}$) and of random effects - *Moving average (MA)*, which have taken place in the past ($a_{t-1}, a_{t-2}, \dots, a_{t-q}$) as shown in Box, Jenkins, and Reinsel (1976); Gaynor and Kirkpatrick (1994.). The emphasis is on using the information in the historical values of a variable for forecasting its future behaviour, and the distribution of future values, conditional on the past (Verbeek, 2008). The specification of an $ARMA(p, q)$ is shown in equation [1], where p and q represent the the number of terms of AR and MA, respectively. The error term a_t is assumed to be a white noise process such that $a_t \sim N(0, \sigma^2)$.

$$Y_t = \phi_0 + \phi_1 Y_{t-1} + \dots + \phi_p Y_{t-p} + a_t + \theta_1 a_{t-1} + \dots + \theta_q a_{t-q} \quad [1]$$

The method of ordinary least square (OLS) is used for the estimation of the model if the series is stationary. Most of the economic series are nonstationary, in which case linear detrending or a differencing filter is used as in Verbeek (2008). An AR and MA process can then be combined into an $ARIMA(p, d, q)$ model as shown in [2], where the integration (I) refers to the number of times that the series has to be differentiated until it is stationary and denoted by Δ^d .

$$\Delta^d Y_t = \phi_0 + \Delta^d \phi_1 Y_{t-1} + \dots + \Delta^d \phi_p Y_{t-p} + a_t + \theta_1 a_{t-1} + \dots + \theta_q a_{t-q} \quad [2]$$

¹The ranking is calculated by the authors in a calendar year.

Box and Jenkins (Box, Jenkins, and Reinsel, 1976) developed a systematic methodology for identifying and fitting a combination of an $ARIMA(p, d, q)$ model. It involves a process of three steps of model selection, estimation and checking. These steps are conducted in an iterative process, that ends with a number of tentative models for the same series. The steps identified by Box and Jenkins are illustrated in Makridakis, Wheelwright, and Hyndman (1998) as shown in Figure 1, followed by a discussion of each phase's procedure.

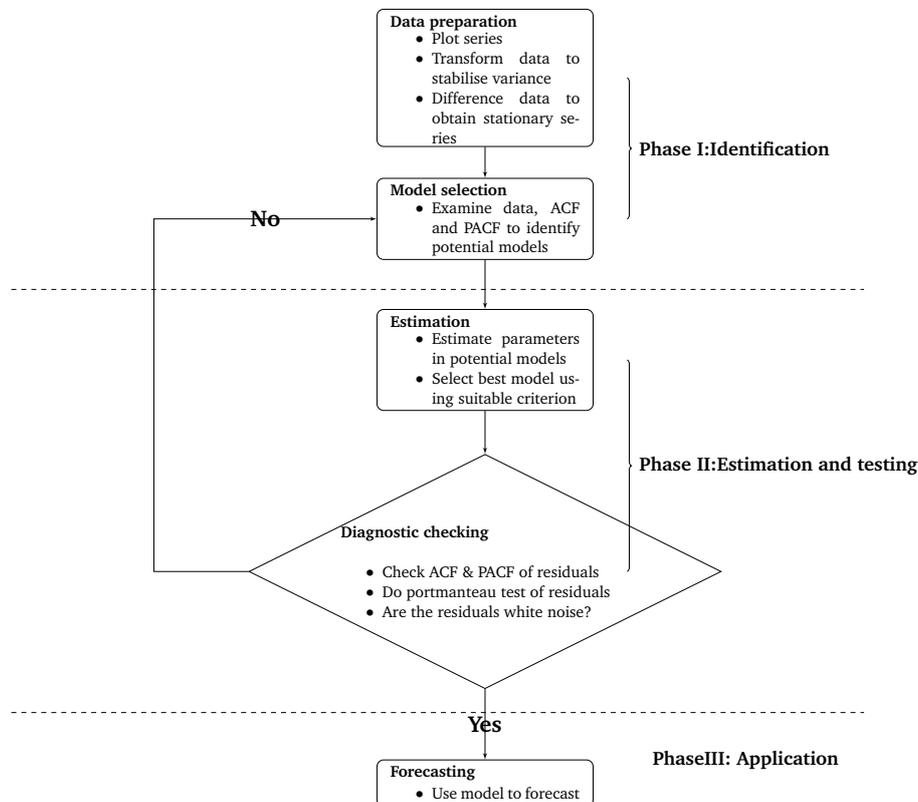


Figure 1: The Box-Jenkins methodology for time series modelling. Source: Makridakis, Wheelwright, and Hyndman (1998) p.314.

2.1 IDENTIFICATION PHASE

This phase is two fold: *first*, to study the time series patterns and identify the degree of integration for the time series by determining the order of d through the Augmented Dickey-Fuller unit root test (ADF). *Second*, to identify the lag order of AR and/or MA terms – p and q respectively– that are needed through the use of correlation coefficients. The Box and Jenkins model-building methodology depends on the pattern of the Autocorrelation Function (ACF) and the Partial Autocorrelation Function (PACF) to identify the order of the (p, d, q) ². The steps followed are:

1. Plotting the time plots, decomposed time series into the different components (trend, random, and seasonal), scatter plots against lagged values and the transformations (like logarithms and first difference).
2. Identifying the difference order of the model, i.e. finding the stationary time

²The ACF(k) measures the correlation coefficient estimated between the time series at lag-zero and its k^{th} -lag. While the PACF(k) measures the coefficients of partial correlation between a time series observations k -lags apart after the correlation at intermediate lags has been controlled (McCleary and Hay, 1980).

series or the order of d .

3. Checking the series for a seasonal regular pattern, if necessary, take appropriate measures. Usually the series is seasonally adjusted before modelling or by multiplicative seasonal models coupled with long-term differencing, if necessary, to achieve stationarity in the mean, as suggested by Box and Jenkins.
4. Determining a few tentative models by analysing ACF and PACF to choose the lag structure.

2.2 ESTIMATION AND TESTING PHASE

For the selected orders of (p, d, q) , the model parameters are estimated for the different tentative models. Once the parameters are estimated, diagnostic checking is required for each of the models, the estimated residuals and the accuracy of holdout sample forecasting. If any of the tests are statistically insignificant, an iterative process starts over another set of tentative models. Moreover McCleary and Hay (1980) mentioned an additional iterative process for the prudent analyses; namely "*metadiagnosis*" where the model is checked for over and under-modelling. A number of tests are conducted to ensure the appropriateness of the selected model:

- test the adequacy and closeness of the model fit to the data,
- test the randomness and the normality of the residuals for example by using the Box-Pierce Statistic or the Jarque-Bera test,
- test the significance and relationships of the parameters, and
- test the model ability to produce reliable forecasts, that is called cross-validation. There are several measures such as the mean square error (MSE), the root mean square error (RMSE) and the mean absolute percentage error (MAPE).

2.3 APPLICATION

If the potential model has passed through all the diagnostic tests, then the selected model will be used to produce out-of-sample forecasts. The interpretation of the results assumes that the same pattern of the time series will hold in the future. An empirical analysis is conducted to the container throughput for the Port of Antwerp in section 3, applying the Box and Jenkins methodology procedure.

3 THE PORT OF ANTWERP CASE STUDY

Given that the port of Antwerp is a major European hub port, and faces the competition from other ports in the Hamburg-Le Havre range, the importance of forecasting arises for short-term operational planning decisions³.

3.1 SAMPLE ANALYSIS

The Box Jenkins methodology is used to forecast the total container throughput (loaded and unloaded) of the port of Antwerp with monthly data measured in units of TEUs, from January 1995 to January 2013, which gives a sample size of 217 observations, denoted by $CTHRP_t$ ⁴.

The sample is split into two sub-samples:

1. The effective sample⁵ starts from January 1995 until May 2010, that is 185 observations that represent about 85% of the sample size.
2. The validation set or the holdout sample starts from June 2010 until January 2013, represents 32 observations and about 15% of the sample size. It is used to evaluate the accuracy of the out-of-sample forecasting performance of the proposed models.

3.1.1 DATA TRANSFORMATION AND GRAPHICAL REPRESENTATION

Transformation of the original series at level is necessary since that the $CTHRP_t$ time series shows changes in levels due to trends (stochastic and/or deterministic) and seasonal effect. Figure 2 depicts the different decomposed components of the time series. It shows an increasing time trend, seasonality, and the random shocks to the container throughput.

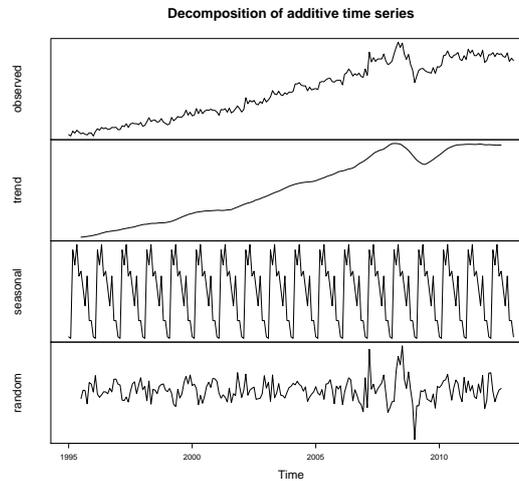


Figure 2: Time series decomposition for Monthly Container Throughput in the Port of Antwerp in TEUs.

³Statistical analyses, models' estimation, and graphical representations were performed using SAS 9.3 software package (SAS Institute Inc., Cary, NC, USA), EViews statistical software package (version 7.1) and R statistical packages R Development Core Team (2008).

⁴The values for the monthly data are not shown under the confidentiality agreement with the Port Authority of Antwerp, nevertheless the analysis is more concerned with the trend of the time series rather than the values.

⁵It is also called the experimental sample or the training set.

Figure 3 depicts the different transformations of the monthly series of container throughput measured in TEUs in the following panels:

- (a) Figure 3a plots $CTHRP_t$: it is the original monthly total container throughput in TEUs at level. The series shows a stable exponential growth until February 2007, starting from March 2007 it is difficult to depict a stable trend.
- (b) Figure 3b displays the natural logarithm of container throughput denoted by $LCTHRP_t$. The logarithmic form is used to stabilise the variance but the series still shows a linear growth path with some fluctuations that may be caused by seasonal effects or shocks to the economy. This might have caused a level shift in trend after January 2009 as a result of the abrupt financial crisis that started in United States of America (U.S.A.) in 2007.
- (c) Figure 3c shows the monthly growth rates for the container throughput measured in TEUs and denoted by:

$$\Delta LCTHRP_t = LCTHRP_t - LCTHRP_{t-1}$$

- (d) Figure 3d shows the monthly series of annual growth rates, that shows more or less regular fluctuations around a stable mean. This series was considered to overcome the problem of seasonality. It is denoted by:

$$\Delta_{12}LCTHRP_t = LCTHRP_t - LCTHRP_{t-12}$$

- (e) To detect outliers, a scatter plot is depicted in Figure 3e of the container throughput at level ($LCTHRP_t$) and the series with one lag ($LCTHRP_{t-1}$).
- (f) Figure 3f presents the scatter plot of $LCTHRP_{t-1}$ versus the first difference of the logarithm of monthly container throughput ($\Delta LCTHRP_t$), which shows the effect of neglecting an outlier on the Dickey-Fuller test as illustrated by Franses (1998).

From Figure 3e and 3f, we conclude that three outliers are suspected in March 2002, March 2007, and January 2009.

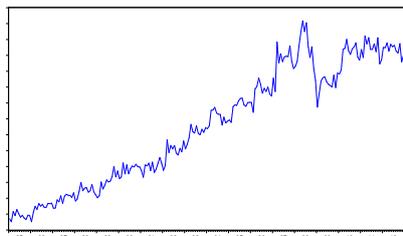
Figure 3c and 3d look like stationary time series that are further tested in the following section. Both do not contain a trend any more and the variance of the monthly throughput changes over time, with volatile periods that move with fluctuations around a long-term stable mean.

3.1.2 TESTING FOR STATIONARITY

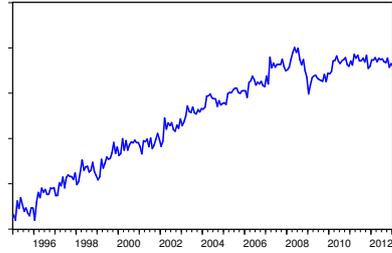
The importance of a stationary time series arises from the necessity of the validation and interpretation of the different test statistics and to avoid spurious regression. A time series is called weak stationary if its statistical properties (mean, variance and covariance between equal lag length) remain constant over time. As elaborated by Heij et al. (2004) in a univariate time series model, it is the correlation with lagged values (autocorrelations of the stationary process) that describe the short-run dynamic relations within the time series. That is in contrast with the trend, which corresponds to the long-run behaviour of the time series.

The tests that are used for the stationarity of the time series are known as the unit root tests. The two most commonly used in the literature are the Augmented Dickey-Fuller test (ADF) (Pindyck and Rubinfeld, 1997) and the Kwiatkowski-Phillips-Schmidt-Shin(KPSS) test (Verbeek, 2008) that are reported in Table A.1.

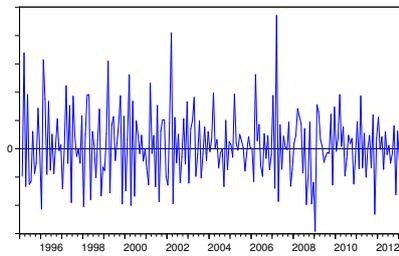
Since time series $LCTHRP_t$ has a unit root, we investigate furthermore whether the time series has two unit roots - that is, we test whether the series $\Delta LCTHRP_t$ of monthly growth rates has a unit root. As the series $\Delta LCTHRP_t$ does not have a clear trend direction, we exclude the deterministic trend component from the ADF test equation. The results reported in Table A.1 show that the ADF and KPSS tests results indicate that $LCTHRP_t$ is stationary at first difference, at 5% significance. Similarly, the same tests are conducted for $\Delta_{12}LCTHRP_t$ and $\Delta\Delta_{12}LCTHRP_t$ to account for the seasonality effect, all the results are shown in Table A.1.



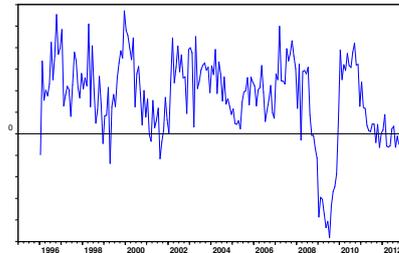
(a) $CTHRP_t$



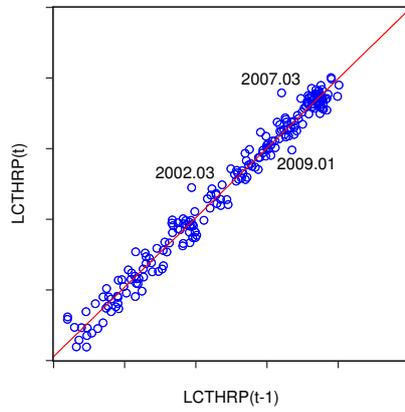
(b) $LCTHRP_t$



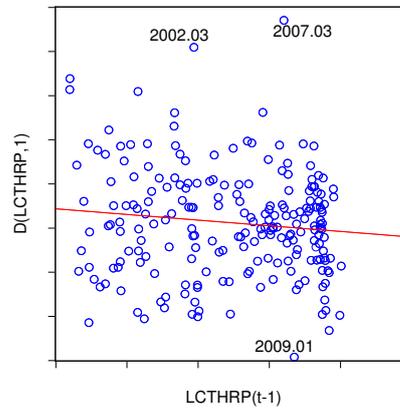
(c) $D(LCTHRP, 1)$



(d) $LCTHRP_t - LCTHRP_{t-12}$



(e) Regression of $LCTHRP_t$ on $LCTHRP_{t-1}$



(f) The effect of neglecting an outlier on the D-F test

Figure 3: Data Transformation for Monthly Container Throughput in the Port of Antwerp in TEUs.

The graphical representation depicted in Figure 4 to test the stationarity for the different transformations is represented by the patterns of the ACF and the PACF. In Figure 4a the ACF plot shows a slow linear decay pattern which is typical of a non-stationary time series, while in Figure 4b the ACF indicates the presence of significant seasonal effects at lag 12, 24 and 36, since it lies outside the 95% boundaries. Similarly, the same figures are plotted for $\Delta_{12}LCTHRP_t$ and $\Delta\Delta_{12}LCTHRP_t$ in Figures 4c and 4d, respectively. Figure 4d shows a dampening of the seasonal effect, where only now the 12th lag is significant.

The overall conclusion is that the $LCTHRP_t$ contains a unit root, while taking the first difference results in the stationary series $\Delta LCTHRP_t$. The modelling of the seasonal component is then dealt with through the series $\Delta\Delta_{12}LCTHRP_t$ that contains no trend and dampening seasonal effect.

3.2 AUTOREGRESSIVE INTEGRATED MOVING AVERAGE MODEL (ARIMA)

3.2.1 IDENTIFICATION PHASE

As concluded from section 3.1.2, both the $\Delta LCTHRP_t$ and $\Delta_{12}LCTHRP_t$ are stationary time series, and hence the pattern of both the ACF and PACF is checked for each series respectively to identify the lag structure and consequently the different tentative models.

The ACF in Figure 4b for the series $\Delta LCTHRP_t$ shows spikes at lags 1, 12, ..., etc. (that emphasise the seasonal effect), while the PACF shows spikes at lags 1, 12 and dampening effects for the other lags. That pattern does not give rise to a definite model. Therefore many models have been considered with reference to the significance of the parameters and the invertibility condition to avoid over-differencing as a selection criterion in addition to Akaike information criterion (AIC) and Bayesian information criterion (BIC) criterion. Different alternative models are tested⁶, where the $ARIMA(2, 1, 1)$ model gives the best fit.

Similarly, the pattern of ACF and PACF for the series $\Delta_{12}LCTHRP_t$ gives rise to a set of different tentative models $AR(2)$, $MA(5)$ and $ARMA(2, 2)$.

3.2.2 MODEL ESTIMATION AND DIAGNOSTIC CHECKING

In this section two models are estimated an $ARIMA(2, 1, 1)$ and an $ARMA(2, 2)$ ⁷, based on the findings of the stationary time series in Section 3.1.2.

The first tentative model is the $ARIMA(2, 1, 1)$ model that is estimated by regressing the first difference of the original series $LCTHRP_t$ on a constant term, two lagged values $\Delta LCTHRP_{t-1}$ and $\Delta LCTHRP_{t-2}$, and one lagged error term. The constant term is originally the slope of a deterministic trend, that after differencing once ($d = 1$), disappears leaving only a level (ϕ_0) around which $\Delta LCTHRP_t$ moves with stationary oscillations. The constant represents the average growth rate of the monthly container throughput measured in TEUs.

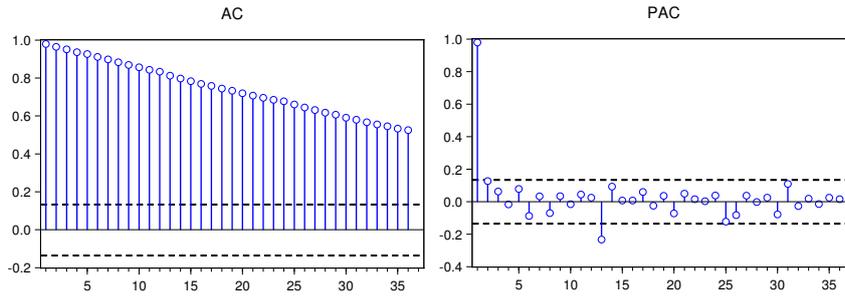
The results are shown in Table A.2 and can be summarized as follows in equation [3] where the asymptotic standard errors of the parameters are in parentheses:

$$\widehat{\Delta LCTHRP_t} = 0.0076 + 0.553\Delta LCTHRP_{t-1} + 0.268\Delta LCTHRP_{t-2} + 0.992a_{t-1}$$

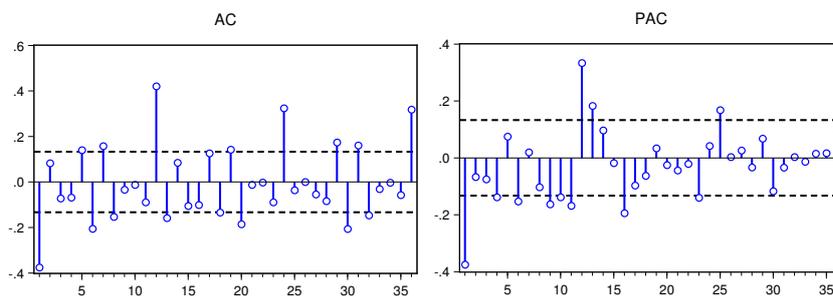
$$\begin{matrix} (0.0005) & (0.0712) & (0.0710) & (0.0106) \end{matrix} \quad [3]$$

⁶Estimates of tentative models are available on request.

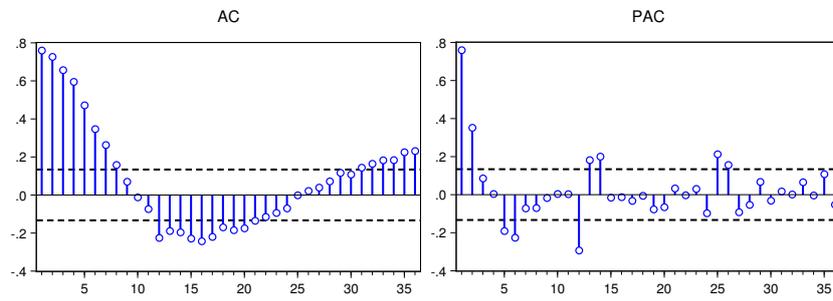
⁷where the dependent variable used in $ARMA(2, 2)$ is $\Delta_{12}LCTHRP_t = LCTHRP_t - LCTHRP_{t-12}$



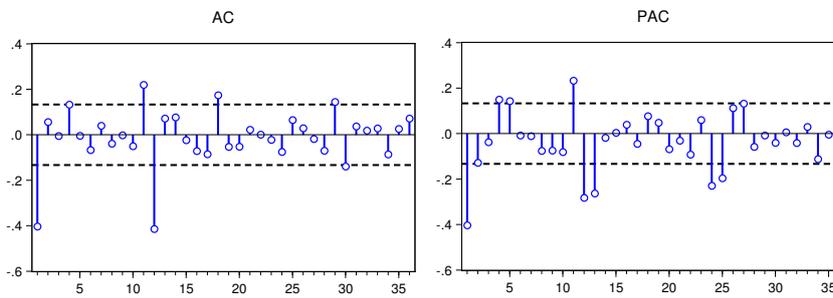
(a) S(P)ACF of logarithmic of container throughput $LCTHRP_t$.



(b) S(P)ACF of first difference of logarithmic of container throughput $\Delta LCTHRP_t$.



(c) S(P)ACF of $\Delta_{12}LCTHRP_t$.



(d) S(P)ACF of $\Delta\Delta_{12}LCTHRP_t$.

Figure 4: The correlograms of the monthly Container throughput transformations. Note: The dashed line represents the 95% confidence interval calculated as $(\pm 1.96/\sqrt{n})$.

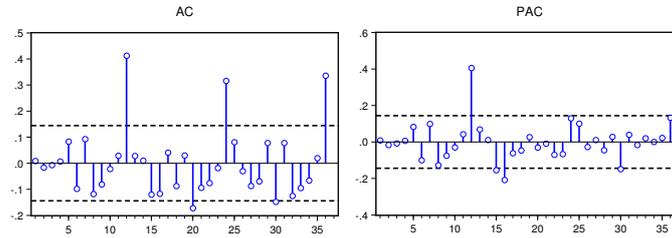
The estimated AR(2) polynomials are factorized; which gives $\phi(z) = (1 - \alpha_1 z)(1 - \alpha_2 z)$ with $\alpha_1 = 0.86$ and $\alpha_2 = -0.31$ reported in Table A.2. so that α_1 and α_2 lie within the unit circle. This provides support for the stationarity of the series.

The second estimated model is an ARMA(2,2) the model estimation output is reported in Table A.3 and the estimated equation is:

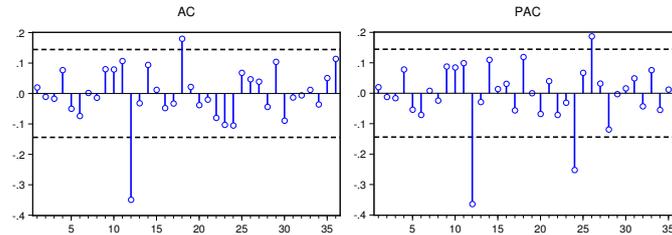
$$\begin{aligned} \widehat{\Delta_{12}LCTHRP}_t = & 0.085 + 1.843\Delta_{12}LCTHRP_{t-1} + 0.268\Delta_{12}LCTHRP_{t-2} \\ & (0.0162) \quad (0.0721) \quad (0.0661) \\ & - 1.453a_{t-1} + 0.628a_{t-2} \\ & (0.0872) \quad (0.0711) \end{aligned} \quad [4]$$

Having estimated the parameters of the two tentative models using $\Delta LCTHRP_t$ and $\Delta_{12}LCTHRP_t$, the validity of the models is checked by different selection criteria and diagnostic tests as shown in Table A.5. According to the model fit, selection criteria, variance and ex ante forecasts, the model ARMA(2,2) performs better. However, for the normality test, the residuals in model ARIMA(2,1,1) are normally distributed, while it is not the case in the model ARMA(2,2).

The serious problem is that both models show serial correlation in the residuals at lags of multiple seasonal effect (12, 24, 36,...,etc). This is shown from the pattern of ACF and PACF in Figure 5. The annual difference $\Delta_{12}LCTHRP_t$ did not account for the seasonal effect, therefore the *Seasonal Autoregressive Moving Average* (SARIMA) is introduced in section 3.3.



(a) S(P)ACF of residual for ARIMA(2, 1, 1).



(b) S(P)ACF of residual for ARMA(2, 2) using $\Delta_{12}LCTHRP_t$ as dependent variable.

Figure 5: The residuals correlogram of the different models.

3.3 SEASONAL AUTOREGRESSIVE MOVING AVERAGE MODEL (SARIMA)

The time series under consideration show an additive seasonal model⁸ that considers a constant amplitude of the seasonal effect from one year to the other. In

⁸Since the logarithmic of the series is used, it is considered a multiplicative seasonal model.

order to deal with seasonality, the ARIMA process is generalized to the model $SARIMA(p, d, q)(P, D, Q)_s$ as shown in Equation [5] expressed in terms of the lag operator as in Box, Jenkins, and Reinsel (1976). Where as previously the (p) refers to the autocorrelation order, the (d) refers to the order of differencing required to make the series stationary and (q) denotes the order of the moving average. The capital letters (P) and (Q) refer to the seasonal model and the (s) denotes the seasonal period. The SARIMA model is generated according to the steps of the Box-Jenkins approach previously outlined in section 2.

$$\phi_p(B)\Phi_p(B^s)\Delta^d\Delta_s^D Y_t = \theta_q(B)\Theta_Q(B^s)a_t \quad [5]$$

Where:

- Y_t : is the time series at level t ,
- B : is the lag operator or backshift operator such that $B(Y_t) = Y_{t-1}$,
 $B^m(Y_t) = Y_{t-m}$, $B^{-m}(Y_t) = Y_{t+m}$, $(1-B)Y_t = Y_t - Y_{t-1}$
and $(1-B)^{-1}Y_t = Y_t + Y_{t-1}$
- Δ_s^D : is the seasonal differencing operator and equal to $(1-B^s)^D$,
- Δ^d : is the nonseasonal operator defined as $(1-B)^d$,
- $\phi_p(B)$: denotes the nonseasonal autoregressive operator of order p
defined as $(1 - \phi_1 B - \phi_2 B^2 - \dots - \phi_p B^p)$,
- $\theta_q(B)$: is the nonseasonal moving average operator of order q
defined as $(1 - \theta_1 B - \theta_2 B^2 - \dots - \theta_q B^q)$,
- $\Phi_p(B^s)$: is the seasonal AR operator of finite order P
- $\Theta_Q(B^s)$: is the seasonal MA operator of finite order Q, and
- a_t : is the white noise, which is assumed to be independently
identically distributed (iid) with zero mean and variance σ^2 .

An empirical analysis is carried out applying the methodology of Box and Jenkins as illustrated in Figure 1, to overcome the problem of serial correlation in the residuals at seasonal lags that arose in the ARIMA model.

3.3.1 IDENTIFICATION

According to the Box and Jenkins methodology, the lag structure of the SARIMA model is based on the pattern of ACF and PACF. The $\Delta\Delta_{12}LCTHRP_t$ shows the seasonal differencing indicated as in Equation [6].

$$\begin{aligned} \Delta\Delta_{12}LCTHRP_t &= (1-B)(1-B^{12})LCTHRP_t \\ &= \Delta LCTHRP_t - \Delta LCTHRP_{t-12} \\ &= LCTHRP_t - LCTHRP_{t-12} - LCTHRP_{t-1} + LCTHRP_{t-13} \end{aligned} \quad [6]$$

The pattern of the ACF and PACF of $\Delta\Delta_{12}LCTHRP_t$ in Figure 4d is difficult to interpret. The ACF shows significant peaks at lag 1 and 12. Furthermore, the PACF displays autocorrelation at lags 1, 11, 12, 13, 24 and 25. Both the ACF and PACF do not display a clear pattern, but suggesting $SARIMA(0, 1, 1)(0, 1, 1)_{12}$ as a tentative model :

$$(1-B)(1-B^{12})LCTHRP_t = (1-\theta_1 B)(1-\Theta_1 B^{12})a_t \quad [7]$$

3.3.2 MODEL ESTIMATION AND DIAGNOSTIC CHECKING

The identification procedure leads to the multiplicative SARIMA specification. The model is estimated in Table A.4 and the diagnostic tests are shown in Table A.5.

The model is complying with reference to the significance of the parameters and the invertibility condition to avoid over-differencing as a selection criterion in addition to the Akaike information criterion (AIC) and the Bayesian information criterion (BIC).

The problem of serial correlation of the residual that was present in ARMA models, is no longer in the SARIMA model, as the probability value of the serial correlation test statistics exceeds 5% as shown from Table A.5.

But the other problem that arises, indicated by the Jarque-Bera test for the model, is that the estimated residual of the model is not normally distributed. that suggests the presence of outliers which was expected from the analysis in Figures 3e and 3f due to the changes in the economic environment and external shocks to the economy.

The abrupt increase in March 2002 was due to a shift of containers by the Mediterranean Shipping Company (MSC) from the Port of Felixstowe to the Port of Antwerp. The significant increase in the time series that started in March 2007 could be linked to the developments in the Port of Antwerp that started in 2005 and continued in 2007. The sharp decline in January 2009 was due to the subprime mortgage crisis that erupted in the U.S.A. in 2007 and spread globally in September 2008.

However, the quantile-quantile plot (Q-Q plot) of the residual in Figure 6 suggests that it might be considered almost normally distributed.

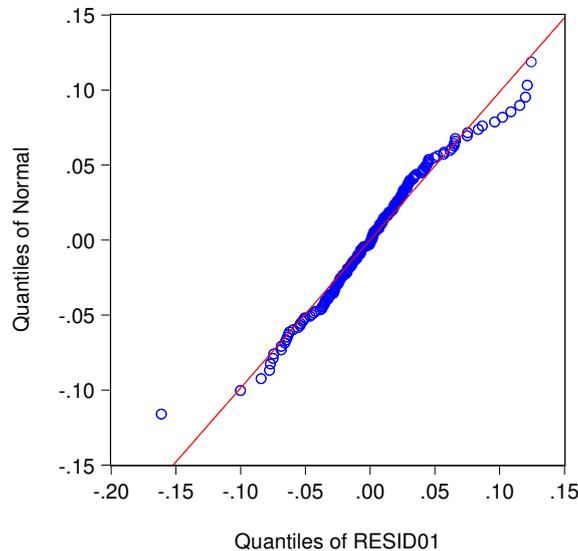


Figure 6: The Q-Q plot of the estimated residual of the $SARIMA(0, 1, 1)(0, 1, 1)_{12}$ model.

The forecasting accuracy criterion used is the mean absolute percentage error (MAPE), which equals 12.29% for the forecast in the holdout sample.

3.3.3 APPLICATION

The estimated model is used to predict the container throughput in the short term (February 2013-December 2014). As shown in Figure 7, the forecasts for 2013 and 2014 are 8.90 and 9.20 million TEUs respectively.

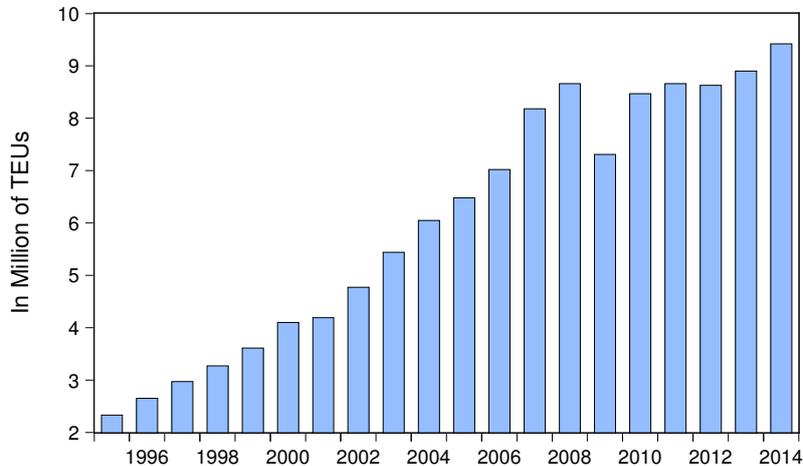


Figure 7: The container throughput for the Port of Antwerp

The existence of three outliers as concluded in section 3.1.1 and shown in Figure 3f, affects the normality test of the residual. For further development in the model under study, the measure of the impact of these shocks on the time series could further be tested through ARIMA models with exogenous variable (ARIMAX) and intervention analysis. Intervention models allow for a rich dynamic structure and proved to be helpful to analyse structural breaks in numerous fields (see Box and Tiao, 1975; Chung, Ip, and Chan, 2009). The type and impact of such shocks are investigated using intervention analysis⁹.

4 CONCLUSIONS

The aim of the univariate analysis applied in this paper is to have insight into the stochastic generating process for the volume of containers in the Port of Antwerp and short-term predictions over the time series where the volume fluctuated during different macroeconomic conditions. The short-term forecasts are essential to the operation and planning of services provided at the port that is of concern for both the Port Authority and port operators. Furthermore, the model represents a simple and a generic way to make short-term forecasts that represents a guide for the public and private policy makers in the short-term. This model represents a primary input for further research and generalisation of the model to include other exogenous variables and test for cointegration relations.

A limitation to this approach is that it does not account for the economic shocks and outliers that might temporarily affect the time series trend or cause a permanent level-shift in the trend. The stochastic process that generates the series shows structural breaks that have to be considered in the development of the model. For

⁹Also known as **impact assessment** (McCleary and Hay, 1980), an **interrupted time series** design in the social sciences (McDowall et al., 1980), or as **transfer functions-noise models** such that the independent variable is substituted by an indicator or a dummy variable to account for the time of intervention (Newbold and Bos, 1990).

further research, the SARIMA model can be generalised to an ARIMAX model that accounts for other leading indicators and intervention analysis. The use of the ARIMAX and the intervention analysis is useful in explaining the dynamics and assessing the impact of the interruptions.

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A APPENDIX

Table A.1: Unit root tests for the different transformations of $CTHRP_t$.

Time Series	ADF test statistic				KPSS		
	H_0 : The time series has a unit root		H_0 : The time series has no unit root		None	Constant & Trend	Constant & Trend
$LCTHRP_t$	P-value	0.9911	0.2633	0.8938	LM-Stat	1.8491	0.3701
	t-statistic	2.0770	-2.0551	-1.2628			
$\Delta LCTHRP_t$	P-value	0.0067	0.0094	0.0123	LM-Stat	0.4070	0.1160
	t-statistic	-2.7142	-3.4825	-3.9362			
$\Delta_{12}LCTHRP_t$	P-value	0.0113	0.0211	0.0012	LM-Stat	0.4645	0.0532
	t-statistic	-2.5319	-3.2050	-4.6281			
$\Delta\Delta_{12}LCTHRP_t$	P-value	0.0000	0.0000	0.0000	LM-Stat	0.0475	0.0452
	t-statistic	-20.6749	-20.6140	-20.5529			
Test Critical Values	1%	-2.58	-3.46	-3.99	1%	0.739	0.216
	5%	-1.95	-2.88	-3.43	5%	0.463	0.146
	10%	-1.61	-2.57	-3.13	10%	0.347	0.119

Remarks:

- The sample used from January 1995 to January 2013.
- The KPSS null hypothesis in case of a constant only is ' H_0 : Stationarity of the time series', while if a trend is included than the null hypothesis is ' H_0 : The time series is trend stationary'.
- The constant is significant and the trend is insignificant for $LCTHRP_t$ and $\Delta LCTHRP_t$.
- The constant and the trend are both significant for $\Delta_{12}LCTHRP_t$.
- The constant and trend are both insignificant for $\Delta\Delta_{12}LCTHRP_t$.
- Both the ADF and KPSS tests fails to reject that $LCTHRP_t$ is stationary. While the tests do not reject that the time series has a unit root for $\Delta LCTHRP_t$ and $\Delta\Delta_{12}LCTHRP_t$, at 5% significance level, respectively.
- The KPSS test shows that $\Delta_{12}LCTHRP_t$ is trend-stationary only.

Table A.2: ARIMA(2,1,1) Model Estimation using $\Delta LCTHRP_t$

Dependent Variable: D(LOG(CTHRP))				
Method: Least Squares				
Sample (adjusted): 1995M04 2010M05				
Included observations: 182 after adjustments				
Convergence achieved after 16 iterations				
MA Backcast: 1995M03				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.007554	0.000503	15.00372	0.0000
AR(1)	0.553236	0.071191	7.771135	0.0000
AR(2)	0.268161	0.071019	3.775912	0.0002
MA(1)	-0.992207	0.010637	-93.27997	0.0000
R-squared	0.176922	Mean dependent var		0.007035
Adjusted R-squared	0.163050	S.D. dependent var		0.061831
S.E. of regression	0.056566	Akaike info criterion		-2.885070
Sum squared resid	0.569557	Schwarz criterion		-2.814652
Log likelihood	266.5414	Hannan-Quinn criter.		-2.856524
F-statistic	12.75384	Durbin-Watson stat		1.975007
Prob(F-statistic)	0.000000			
Inverted AR Roots	.86			
Inverted MA Roots	.99			

Table A.3: ARMA(2,2) Estimation using $\Delta_{12}LCTHRP_t$ as a dependent variable

Dependent Variable: LOG(CTHRP)-LOG(CTHRP(-12))				
Method: Least Squares				
Sample (adjusted): 1996M03 2010M05				
Included observations: 171 after adjustments				
Convergence achieved after 22 iterations				
MA Backcast: 1996M01 1996M02				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.084530	0.016175	5.225980	0.0000
AR(1)	1.842853	0.072072	25.56979	0.0000
AR(2)	-0.889436	0.066113	-13.45327	0.0000
MA(1)	-1.453039	0.087248	-16.65404	0.0000
MA(2)	0.627558	0.071123	8.823505	0.0000
R-squared	0.665131	Mean dependent var		0.084023
Adjusted R-squared	0.657062	S.D. dependent var		0.095563
S.E. of regression	0.055963	Akaike info criterion		-2.899464
Sum squared resid	0.519880	Schwarz criterion		-2.807603
Log likelihood	252.9042	Hannan-Quinn criter.		-2.862191
F-statistic	82.42909	Durbin-Watson stat		1.955106
Prob(F-statistic)	0.000000			
Inverted AR Roots	.92-.20i			
Inverted MA Roots	.73-.32i			

Table A.4: $SARIMA(0, 1, 1)(0, 1, 1)_{12}$ Model Estimation using $\Delta\Delta_{12}LCTHR_t$

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Dependent Variable: D(LOG(CTHRP),1,12)				
Method: Least Squares				
Sample (adjusted): 1996M02 2013M01				
Included observations: 204 after adjustments				
Failure to improve SSR after 10 iterations				
MA Backcast: 1995M01 1996M01				
MA(1)	-0.417740	0.050350	-8.296771	0.0000
SMA(12)	-0.926109	0.012108	-76.48986	0.0000
R-squared	0.568908	Mean dependent var		-2.47E-05
Adjusted R-squared	0.566774	S.D. dependent var		0.063580
S.E. of regression	0.041848	Akaike info criterion		-3.499780
Sum squared resid	0.353757	Schwarz criterion		-3.467249
Log likelihood	358.9775	Hannan-Quinn criter.		-3.486621
Durbin-Watson stat	1.972016			
Inverted MA Roots	.99	.86+.50i	.86-.50i	.50+.86i
	.50-.86i	.42	.00+.99i	.00-.99i
	.50+.86i	.50-.86i	-.86-.50i	-.86+.50i
	-.99			

Table A.5: Overview of Diagnostic Tests for the different tentative models.

Dependent Variable	$\Delta LCTHRP_t$	$\Delta_{12} LCTHRP_t$	$\Delta \Delta_{12} LCTHRP_t$
Criterion	ARIMA(2, 1, 1)	ARMA(2, 2)	SARIMA(0, 1, 1)(0, 1, 1) ₁₂
Model fit			
R-squared	0.176922	0.665131	0.568908
Adj R-squared	0.16305	0.657062	0.566774
Sum Squared Residual	0.569557	0.51988	0.353757
Std. Dev. of Residuals	0.056015	0.055297	0.041717
Inverted AR and/or MA roots	<1	<1	<1
Selection Criterion			
AIC	-2.88507	-2.899464	-3.49978
SIC	-2.814652	-2.807603	-3.467249
Normality of Residual			
Skewness	0.378249	-0.087561	0.157845
Kurtosis	4.46699	3.17497	4.418795
Probability of Jarque-Bera test	0.000033	0.80387	0.000126
Variance of Residual	ARCH Test Prob. of $\chi^2(1)$	0.8046	0.0917
Serial Correlation of Residual	Ljung-Box (36 lags)	0.0000	0.5470
Residual (Probability)	Breusch-Godfrey (12 lags)	0.0000	0.4678
Ex-post Forecast (2010.06-2013.01)			
RMSE of Static Forecast	44208.97	26281.83	25693.43
RMSE of Dynamic Forecast	200008.60	87161.83	106414.50
MAPE of Static Forecast	5.290573	2.845863	2.827873
MAPE of Dynamic Forecast	25.636960	10.166130	12.288160

(a) Jarque-Bera test null hypothesis is that the residuals are normally distributed.

(b) Autoregressive conditional heteroscedasticity test(ARCH) null hypothesis is that the residuals are homoscedastic, i.e. have constant variance.

(c) The Ljung-Box test also known as Q-statistic or a portmanteau test that considers the significance of autocorrelation collectively at a set of lags.

(d) The Breusch-Godfrey test null hypothesis is that there is no serial correlation in the residuals, i.e. the series is a white noise.

(e) The root mean square errors (RMSE) and the mean absolute percentage error (MAPE) are measures of ex-post forecast accuracy.

RMSE is measured in units of $LCTHRP_t$ (in TEUs) and MAPE is scale invariant. Defined as: $RMSE = \sqrt{\frac{1}{n} \sum_{t=1}^n e_t^2}$ and $MAPE = \frac{1}{n} \sum_{t=1}^n \left| \frac{e_t}{\hat{y}_t} \right| \times 100$.