Short-term forecast of container throughout : an ARIMA-intervention model for the port of Antwerp

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Abstract

Short-term forecasts of container throughput are essential for planning both port operations and hinterland activities. However, the volatility and uncertainty in the global conditions of the economic activity and, consequently, the seaborne trade impose complexity in modelling and forecasting container throughput at the port level. In this paper, different univariate time series approaches were applied; the autoregressive integrated moving average (ARIMA) model, namely the ARIMA-intervention model, and the ARIMAX model with leading economic indicator. The advantage of the methodology applied is two-fold; (i) it provides insight about the data generating process post-2008 financial crisis and (ii) it identifies the relationship between the economic activity and the container throughput. Monthly data for the total container throughput at the port of Antwerp was used for the period January 1995 - March 2015. Based on the empirical analysis and the assessment of the forecasting performance, the EU industrial confidence indicator turned out to lead the container throughput for two months. In addition, the incorporation of the structural break of October 2008 showed that, given the conditions, the container throughput was persistent to return to the pre-crisis level.

Keywords: ARIMA; container throughput; transport

modelling; forecasting; intervention analysis; Port of Antwerp.

Introduction

Short-term decisions play an important role in the development of the port's competitive position and the direct and indirect effects on the economy. The short-term decisions by terminal operators, port authorities and other stakeholders concerning the planning of operations, as well as resource allocation decisions in order to avoid congestion and handle the volume of containers in an efficient way not only at the terminals, but also on the connections with the hinterland.

The port activity is closely related to the changes in the global economy. The global financial crisis in 2008 had a significant impact on the port sector. Therefore, port authorities, terminal operators, investors and other stakeholders rely on the demand traffic forecasts to rationalise decisions related to operation and investment. The aim of this paper is to provide a planning instrument to cope with the uncertainty and volatility of the short-run fluctuations of the future demand.

The developed model is to forecast the short-run container throughput at the port level, measured in twenty-foot equivalent units (TEU) instead of tonne, that is often used in the literature and previous models. Moreover, the analysis is conducted ex post the 2008 financial crisis that is incorporated in the model, which provides insight into the data generating process after a structural break and quantifies the impact on the container throughput during and after the shock. In addition, the model identifies exogenous variables that lead the container throughput. These are all new and original contributions to the current state of knowledge.

The importance of these forecasts is of interest to terminal operators and port authority, since the operational decisions and services provided depend on the number of container movements per unit of time. Nevertheless, forecasting using the number of TEU imposes restrictions, since it is not always representative of the country's economic activity. The container throughput does not necessarily reflect the trade volume nor the economic activity. That imposes a challenge to identify the relationship between the economic activity and the container throughput.

Therefore, our methodology relies upon univariate time-series methods. Two dynamic time series modelling approaches are applied in this paper. First, an autoregressive integrated moving average (ARIMA) model is estimated, combining seasonality with the intervention function to account for the effect of shocks. Second, an ARIMAX (ARIMA with exogenous variable) model is estimated to account for the relationship between port throughput and economic activity. The advantage of univariate modelling is that it offers a systematic approach to building, analysing, and forecasting time series models, independent of other variables that are needed in multiple regression analysis.

The structure of this paper is as follows. A literature review is presented, followed by the methodology for building the model. Next, the empirical analysis of the port of Antwerp is conducted. Finally, the discussion of the results and main findings is given and conclusion and further research are presented.

Literature Review

Econometric models in forecasting are extensively used in the financial and macroeconomic analysis, measuring among others the impact of policy change and structural shocks. Meersman et al. (2002) reviewed extensively the literature, for the period 1970 to 1997, on forecasting total port demand. Most of the studies conducted during this period were based on expert opinions and trend extrapolation using the GDP and trends in exports and imports, with only a few of them showing the specified models used. Forecasting methods assuming a relation between GDP and port throughput have been extensively used in the literature, albeit assuming a stable relationship between the two variables. In practice however, this relationship is changing due to changes in production, trade patterns, increasing transhipment activities, and supply chains and logistics services that cause the rise and fall of different ports.

Applying a univariate approach to forecasting seaborne trade is found in the work of Klein (1996). He showed that using transformations and intervention models at a disaggregate commodity level provides useful insights into the behaviour of the time series and accounts for outliers in it. In order to forecast the cargo flows at the port of Antwerp, he studied the volumes of 22 commodity flows during the period 1971-1982. The range of the commodities in his analysis varied widely between general and bulk cargo (loading and unloading) expressed in tonnes. The intervention approach used in Klein (1996) depended on the piecewise linear functions (Melard, 1981) rather than the output response (Box et al., 1975) applied in this paper.

A comparison of six univariate models was conducted and applied to three major ports in Taiwan, for monthly time series, by Peng and Chu (2009), to forecast container throughput. They concluded that the classical decomposition method and the seasonal autoregressive integrated moving average (SARIMA) model give the best forecast, based on the forecasting accuracy criterion. However, the value added of using the ARIMA method in our paper is that it incorporates intervention parameters and exogenous variables.

For the long run, other approaches have been applied that depend on causal methods. A multivariate autoregressive model is used in Veenstra et al. (2001) to forecast the long-term trade flow at commodity level. Fung (2002) estimated an error correction model for the terminals at the ports of Hong Kong and Singapore to study the competitive interaction between terminal operators. The author emphasised the dependence of the forecasts on the interaction between ports, and provided a systematic approach to forecasting the demand for container handling services. A multiple regression model was used to investigate the long and short-run relations between exports and imports and a port's loading and unloading activities, respectively in Meersman et al. (2003) and Meersman et al. (2013). The work of De Langen (2003) identified seven determinants of maritime container transport demand, where four factors are related to the volume and flow of trade and three related to the containerised share of transport flows. Hui et al. (2004) forecast the port cargo throughput in Hong Kong by estimating a cointegrated error correction model.

In other transport sectors, such as air transport, Lai et al. (2005) used an intervention-ARIMA approach, incorporating the September 11, 2001 shock, to measure the impact of that shock on the number of passenger and forecast air travel passenger demand in the US. In the manufacturing sector, Chung et al. (2009) estimated an ARIMA-intervention model to investigate the impact of a sudden financial crisis on the manufacturing industry in China. Other qualitative analyses are found in Pallis et al. (2010), providing an analysis for the structural implications of the economic crisis on ports, and the analysis of Slack (2010), who investigates the major impacts of the financial crisis on maritime industries. Gröger et al. (2011), study the intervention analysis in ecological applications, distinguishing between a regime shift that causes a structural break in the data and a regime shift due to the natural periodic cycles.

From the previous literature review, we conclude that the choice of the appropriate forecasting model depends on the purpose, the forecasting period, exogenous factors affecting that period, the type of cargo and the structure of the time series.

The Methodology

The standard univariate common technique followed in the literature and adopted in the present analysis is the Box-Jenkins methodology (Box et al., 1976). The Box-Jenkins procedure uses past values of a time series variable in combination with present and past values of random shocks to forecast the variable. This method is justified by the fact that the observations measured over time are not independent, i.e. they often show strong autocorrelation. The empirical model is achieved through a series of iterative processes of model specification, estimation, diagnostic testing, and model adjustment. This procedure is carried out on stationary time series, assuming a linear behaviour of the series. Both the seasonal ARIMA-intervention model and the ARIMAX model are estimated to forecast the short-term container throughput at port level. We compare the results to determine which model gives a better forecast.

Box et al. (1976) developed a systematic empirical approach for identifying and fitting a rigorous model, that can be statistically reliable and validated. This involves a process of three steps: (1) model identification, (2) estimation and diagnostic testing, and (3) the application to forecasting. These steps are conducted in an iterative process, suggesting a number of tentative models. For these, the parameters are estimated, followed by a number of diagnostic tests and visual inspections conducted to ensure: (a) the adequacy of model fit to the data, (b) the significance of the parameters and the satisfaction of the invertibility condition, (c) the randomness of the residuals, and (d) cross-validation to check the models' ability to produce reliable forecasts, whereby the mean absolute percent error (MAPE) is calculated to measure the forecasting accuracy of the holdout sample. Once a potential model has passed all diagnostic tests, it is selected and used to produce *ex ante* *forecasts*, comparing the forecasting error to ensure a dynamic instrument for operational decision making.

The ARIMA Model

The Box-Jenkins procedure uses past values of a time series variable - *autoregressive (AR)*, $(y_{t-1}, y_{t-2}, \dots, y_{t-p})$ - in combination with past values of random shocks - *moving average (MA)*, $(a_{t-1}, a_{t-2}, \dots, a_{t-q})$. The emphasis is on using the information contained in the historical values of a variable for forecasting its future behaviour, and the distribution of future values, conditional on the past (see Verbeek, 2008). The Box-Jenkins methodology is carried out on a stationary time series data, where *(I)* denotes the order that the series has to be differenced until it is stationary.

An important characteristic of the monthly time series data used is *seasonality*. In order to deal with this, the ARIMA model is extended to the $SARIMA(p,d,q)(P,D,Q)_s$ model, where the *(s)* stands for 'seasonal'. In Equation 1, the SARIMA model is expressed in terms of the lag operator, where *(p)* refers to the autocorrelation order, *(d)* refers to the order of differencing, and *(q)* denotes the order of the moving average. The capital letters *(P,D,Q)* refer to the seasonal components, respectively.

$$\emptyset_p(B)\Phi_p(B^s)\Delta^d\Delta_s^D Y_t = \theta_q(B)\Theta_Q(B^s)a_t \tag{1}$$

where

Y_t : is the time series at level t

B : is the lag operator

Δ_s^D : is the seasonal differencing operator, equal to $(1 - B^s)^D$

Δ^d : is the nonseasonal operator defined as $(1 - B)^d$

$\emptyset_p(B)$: is the nonseasonal autoregressive operator of order *p* defined as $(1 - \emptyset_1 B - \emptyset_2 B^2 - \cdots - \emptyset_p B^p)$

$\theta_q(B)$: is the nonseasonal moving average operator of order *q* defined as $(1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_p B^p)$

$\Phi_p(B^s)$: is the seasonal AR operators of finite orders P

$\Theta_Q(B^s)$: is the seasonal MA operators of finite orders Q

a_t : is the white noise, assumed to be independently identically distributed (iid) with zero mean and variance σ^2.

The cross-correlation function (CCF) is used to test for the different economic variables to be included as an exogenous variable in the framework of the ARIMAX. To identify the lead-lag relationship, the CCF is used on a stationary time series. The sample CCF is defined in terms of the cross-covariance function (CCVF) as follows (see Chatfield, 2004, pg. 155-159):

The sample CCVF is:

$$c_{xy}(k) = \begin{cases} \sum_{t=1}^{n-k} (x_t - \mu_x)(y_{t+k} - \mu_y) / n, & k = 0,1, \dots, n-1 \\ \sum_{t=1-k}^{n} (x_t - \mu_x)(y_{t+k} - \mu_y)/n, & k = -1, -2, \dots, -(n-1) \end{cases} \quad (2)$$

Note that in Equation (2) the first line refers to (x leads y or y lags x), and the second one refers to the converse.

The sample CCF is:

$$\rho_{xy}(k) = \frac{c_{xy}}{\left(\sigma_x^2 \sigma_y^2\right)^{1/2}} \quad (3)$$

Where,

n: is the sample size

k: is the lag number

μ_x: is the mean of x_t

μ_y: is the mean of y_t

σ_x^2: is the variance of x_t, and

σ_y^2: is the variance of y_t

Intervention Analysis

The presence of outliers in the observed series can cause biased estimation of the autoregressive coefficients, resulting in forecasting bias and larger corresponding forecasting intervals. The problem gets worse when the outliers are close to the forecasting origin (Franses, 1998). Outliers and innovations are exploited explicitly, not only for purposes of forecasting accuracy and unbiased estimation, but also because they might convey important information to policy makers about the data generating process.

In the works of Box et al. (1975), Tsay (1986), and Franses (1998) a distinction was made between outliers and intervention variables. On the one hand, an outlier, or an *additive* outlier is an anomaly in the time series, due to non-economic reasons with no prior information on the date of their occurrence, only affecting the mean function at the time of occurrence without changing the generating process. On the other hand, an *intervention,* or an *innovation outlier* is defined as any event with prior information, occurring between two time periods and expected to cause abnormal observations, or a change in the generating process of the time series that affects the trend of the process. A shock is caused by an exogenous intervention such as a policy change, a crisis, or any other external factor.

The empirical analysis adopted here depends on the interaction of two criteria; (1) *duration* -- whether it is a temporary or a permanent effect and (2) *the impact effect* -- if the change is in the level or the slope or both. The general form of the dynamic intervention analysis model for a time series with (k) outliers occurring at time ($\mathrm{T_i}$) where ($\mathrm{i} = 1,2, \dots, \mathrm{k}$) is represented by Equation (4) as suggested by Box et al. (1976):

$$Z_t = m_t + y_t \tag{4}$$

Where (Z_t) is the observed contaminated series, (y) is the unperturbed process but unobserved time series and (m_t) is the transfer function. The transfer function models the impact of outliers such that:

$$m_t = \sum_{i=1}^{k} V_i(B) w_i I_t^{T_i} \qquad (5)$$

where,

$V_i(B)$: represents the dynamic impact of the outlier *i* at time *T*

w_i : is the magnitude (coefficient) of the impact

T_i : occurrence time of the intervention or outlier, and

$I_t^{T_i}$: is an indicator/intervention variable with choices as:

$$P_t^T = \begin{cases} 1, & if\ t = T \\ 0, & otherwise \end{cases} \qquad \text{'pulse intervention'} \qquad (6a)$$

$$S_t^T = \begin{cases} 1, & if\ t \geq T \\ 0, & otherwise \end{cases} \qquad \text{'step intervention'} \qquad (7b)$$

The unperturbed process y_t is such that:

$$\pi(B) y_t = a_t$$

$$\pi(B) = \frac{\emptyset_p(B)\alpha(B)}{\theta_{q(B)}}$$

$\alpha(B) = (1 - B)^d (1 - B^s)^D$ and hence

$$Z_t = \begin{cases} y_t, & if\ t \neq T \\ y_t + \sum_{i=1}^{k} V_i(B) w_i I_t^{T_i}, & if\ t = T \end{cases}$$

Based on the dynamic impact of the outlier, the $V_i(B)$ can take different forms; an additive, an innovation, a permanent or a transient level shift and a changing trend, as defined in Fox (1972), Box et al. (1976), Tsay (1986), Tsay (1988), and Franses (1998). For example, if the short-lived intervention effects are specified using a pulse response intervention as defined in Equation (6a), these effects might die out gradually. At the same time, the step response intervention as defined in Equation (6b), represents the impact that affects the mean function.

Empirical Analysis

The port of Antwerp is located centrally within the Hamburg-Le Havre range. In 2014, the port captured approximately 22% of the container market of the main container ports in the Hamburg-Le Havre range. It is Europe's second largest port by total throughput (199 million tonnes) and third in terms of container throughput (9 million TEU) in 2014. Port activities and their impact on the national economy are thus significant. In 2013, the port of Antwerp's share of direct and total value added in the Belgian GDP was 2.5% and 4.8% respectively, while employment represented 1.5% (direct) and 3.7% (total) of Belgian employment (Van Nieuwenhove, 2015).

Data Analysis and Model Identification

Our analysis is based on a time series of monthly total container throughput (loaded and unloaded), measured in TEU, from January 1995 to March 2015, denoted by $CTHRP_t$; an index number is used instead of the actual monthly container throughput due to a confidentiality agreement with the port of Antwerp so as not to conceal the monthly figures. During that period, the average loading/unloading ratio was approximately 0.50. The highest average month has been March, attributed to the effect of the Chinese New Year, when the Asia-Europe trade is significant. The sample is split into two sub-samples for estimation and validation purposes: (1) *the experimental set*; starting in January 1995 to March 2011 and representing about 80% of the sample size; and (2) *the validation set*, starting in April 2011 to March 2015 and representing about 20% of the sample size. The sample is visualised in Figure 1.

Figure 1: Port of Antwerp monthly container throughput in TEU.

Figure 1 shows a linear behaviour of the series with stable exponential growth until Oct. 2008 (time of break 'TB') when the real estate crisis in the US emerged. This led to a structural break that caused a change in the rate of growth, becoming evident in Jan. 2009. The lag is attributed to the time delay between the outbreak of the crisis and its impact on container throughput. This is shown by the two different growth paths. The *trend line* is estimated from the regression on a constant and a trend (t) and the *break in trend line* is estimated with the addition of a dummy variable, taking zero prior and *at* TB, and (t-TB) afterwards. It is shown that the break is close to the end points of the experimental set which imposes limitations on the model estimation and the ability to forecast. Moreover, during the period Mar. 2007 - Mar. 2010, it is difficult to depict a stable behaviour since many interruptions occurred. Analysing the significant changes, the following factors are identified:

- The peak in March 2002 was due to a substantial shift of container flows by the Mediterranean Shipping Company (MSC) in the first quarter of 2002 from the Port of Felixstowe to the port of Antwerp (see Coppens et al., 2007, p.1). This is modelled by an additive outlier '*Mar02'* of a temporary pulse effect, since the random component was not affected by such a change.

- The jump in March 2007 is related to the new port capacity and operational developments in the port during 2005-2008 (Flemish Port Commission annual reports). The container terminal 'Antwerp Gateway' opened in March 2005 in the eastern part of the Deurganck dock, followed by the joint venture between PSA Corporation Ltd (PSA) and MSC at the Delwaide dock in June 2005. In 2006, a new fully automated fruit terminal was built and the 'Antwerp International Terminal' in the western part of the Deurganck dock was opened (currently it is the 'PSA terminal'). In 2008, some liner shipping companies rescheduled their services and added Antwerp more frequently as a port of call. These developments are reflected by an innovation outlier '*Mar07'* as input in March 2007 with an instantaneous increase in the *CTHRP* of $(\widehat{\omega_\iota})$ above the current mean level at time *(T)* and propagating in the subsequent observations until August 2008.
- That booming period came to an end in the last quarter of 2008 as a result of the financial crisis that broke out in the USA in 2007. That resulted in a declining world trade and consequently dropping container volumes on all routes, with a particularly sharp decline on the Europe - Far East route. Therefore, '*Oct08'* is defined as a temporary shift; with a pulse input in Oct. 2008,

having an initial negative change of $(\widehat{\omega_2})$ that decays exponentially and stabilises at the original trend to the pre-intervention level by a factor of $\hat{\delta}$.

Different transformations of $CTHRP_t$ are tested for stationarity. The tests used are the Augmented Dickey-Fuller test (ADF) and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test (see Pindyck et al., 1997; Verbeek, 2008). The $Log(CTHRP_t)$ is found to be stationary of order one, i.e. *(1)*. However, there are significant coefficients at the seasonal lags. To overcome this, we examine the autocorrelation function (ACF) and partial autocorrelation function (PACF) of the series $\Delta\Delta_{12}CTHRP_t$ that shows a dampening seasonal effect. As a consequence, model estimation is carried out using $\Delta\Delta_{12}CTHRP_t$.

Rashed et al. (2013) concluded that a seasonal autoregressive integrated moving average of order ARIMA $(0,1,1)(0,1,1)_{12}$ model is the appropriate one for the container throughput time series among the other tentative models estimated. The tests show that the eliminated models either do not satisfy one or all of the residual diagnostic tests (variance constancy and heteroscedasticity, normality and stationarity) and/or the invertibility condition, or, for those who satisfy the tests, the final selection criteria was based on the minimum Akaike information criterion (AIC) and the significance of the parameters.

Model Estimation

The SARIMA(0,1,1)(0,1,1)$_{12}$ was estimated by the maximum likelihood method (Equation 7). Model estimates are reported in Table 1.

$$Z_t = y_t + w_0 Mar02 + \frac{1}{\pi(B)}[w_1 Mar07] + \frac{w_2}{1-\delta B} Jan09 \qquad (7)$$

The estimates in Table 1 show that the additive outlier in March 2002 had an effect of an approximately 9% increase in the mean of the series [calculated as: $(e^{0.095} - 1)x100$]. The intervention in March 2007 is interpreted as an increase of 9% in container volume above the general trend associated with the introduction of the new developments (opening of the new terminals 'Antwerp Gateway' and the 'Antwerp International Terminal' as well as the joint venture between PSA and MSC). Moreover, the financial crisis led to an abrupt temporary change with a slow decay rate to the original level $\delta = 0.92$ that reduced the container throughput by an asymptotic change of approximately 16% [calculated as: $(e^{-0.172} - 1)x100$]. The hypothetical inference of the expected filter of the financial crisis is that after 3 years the impact of the crisis is still approximately 0.85% [calculated as: $(1 -$

$e^{-0.172x0.92^{36}})x100]$. This is consistent with the empirical evidence, showing that the recovery started in March 2010.

Table 1: Estimation of SARIMA(0,1,1)(0,1,1)$_{12}$-Intervention model (1995.01-2015.03).

	$\widehat{\theta_1}$	$\widehat{\Theta_{12}}$	$\widehat{\omega_0}$	$\widehat{\omega_1}$	$\widehat{\omega_2}$	$\hat{\delta}$
Estimate	-0.5569	0.7988	0.0903	0.0887	-0.1723	0.9160
Pr(>ltl)	<0.0001	<0.0001	0.0048	<0.0001	<0.0001	<0.0001
SE	(0.0555)	(0.0505)	(0.0320)	(0.0213)	(0.0314)	(0.0564)

Furthermore, the model without intervention analysis is estimated too. The MAPE for the validation set of the different models is reported in Table 2, which shows that the error is lower in the ARIMA model with no intervention. However, the two models are estimated using the full sample, where the ARIMA intervention model shows lower MAPE. The different results are attributed to the fact that the US financial crisis occurred closer to the end of the training sample period, while in the full sample there is enough time for the intervention adjustment to take effect. The advantage of the ARIMA intervention model is not only in forecasting, but also the interpretation of the intervention parameters is important in giving an estimation of the extent of the impact of different changes.

Table 2: Comparison of the forecast accuracy for the model estimation using the training and full sample

Model	Sample of estimated model	MAPE
ARIMA	Training	6.73%
ARIMA intervention		7.53%
ARIMA	Full	3.28%
ARIMA intervention		3.16%

ARIMAX Model

The ARIMAX model depends on finding an exogenous variable that leads the container throughput. On the assumption that there exists a relationship between economic activity and container throughput, the cross-correlation function is used to test this relationship for different economic variables. The industrial confidence indicator (Eurostat, 2015) for the Euro Area (ICI_EA) with two lags shows the best fit as a leading indicator. This can be explained by the fact that the port of Antwerp provides a widespread hinterland access by means of road, inland navigation, and rail mainly to The Netherlands, Germany and France. Estimates of the model are shown in Table 3.

Table 3: ARIMAX$(0,0,1)(0,0,1)_{12}$ with exogenous variable ICI_EA_{t-2}

Dependent Variable: CTHRP-2688.785*@TREND+1
Method: Least Squares

Date: 06/08/15 Time: 11:45
Sample (adjusted): 1995M03 2015M03
Included observations: 241 after adjustments
Convergence achieved after 12 iterations
MA Backcast: 1994M02 1995M02

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	194378.6	4944.642	39.31096	0.0000
ICI_EU19_EA(-2)	2652.653	344.2185	7.706304	0.0000
MA(1)	0.535023	0.055203	9.691901	0.0000
SMA(12)	0.506191	0.056930	8.891505	0.0000

R-squared	0.635017	Mean dependent var	179625.0
Adjusted R-squared	0.630397	S.D. dependent var	50506.08
S.E. of regression	30705.15	Akaike info criterion	23.51871
Sum squared resid	2.23E+11	Schwarz criterion	23.57655
Log likelihood	-2830.004	Hannan-Quinn criter.	23.54201
F-statistic	137.4487	Durbin-Watson stat	1.446344
Prob(F-statistic)	0.000000		

Inverted MA Roots	.91-.24i	.91+.24i	.67+.67i	.67-.67i
	.24-.91i	.24+.91i	-.24-.91i	-.24+.91i
	-.54	-.67-.67i	-.67-.67i	-.91+.24i
	-.91-.24i			

The actual and forecast throughput and the 95% confidence interval is shown in Figure 2, where the MAPE is 4.97%.

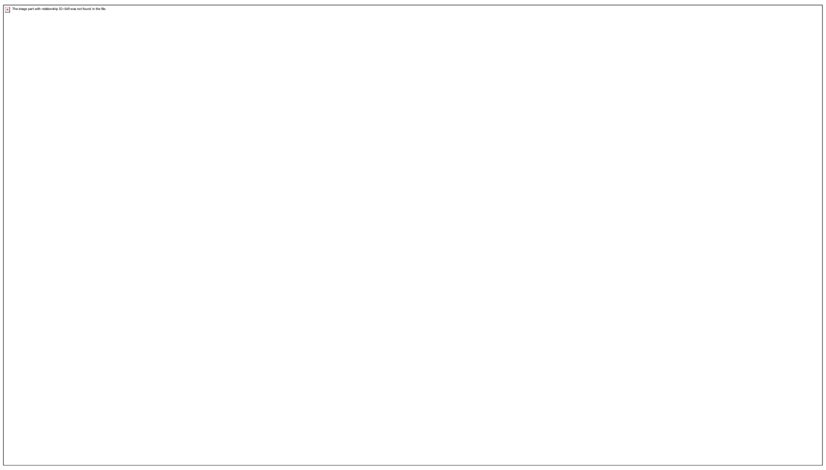

Figure 2: ARIMA(0,0,1)$(0,0,1)_{12}$ model - with exogenous variable.

Results and Discussion

The problem in modelling the container throughput arises because the dynamic process of the time series is significantly interrupted. This is shown in Figure 3 that analyses the year-to-year monthly growth rate. During the period Jan. 1995 - Oct. 2008, the monthly year to year growth rate was stable around 11%. That declined sharply to -15% during the period Oct. 2008 - Nov. 2009. The analysis shows a stagnant growth rate that fluctuates around a mean of -0.12% over the period Aug. 2011 - Apr. 2014. Most of these fluctuations are attributed to the economic activity and trade, other factors including the competitive position of the port.

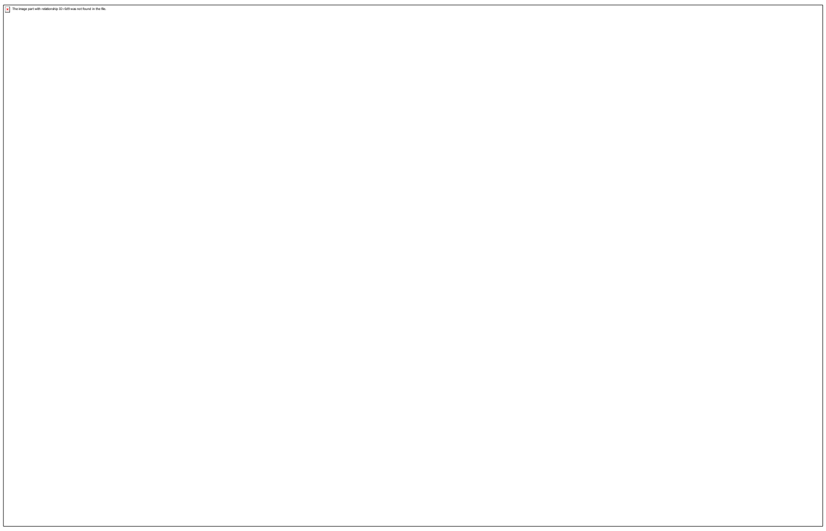

Figure 3: Container throughput (y-o-y) monthly growth rate.

The comparison of the models shows that ARIMAX provides the lowest MAPE for the validation sample Apr. 2011 - Mar. 2015; ARIMA (19.58%), ARIMA with intervention (23.38%) and ARIMAX (6.22%). Figure 4 shows the forecast comparison of the three models. For the short-term of 12 months, the ARIMA model provides forecasts of 5.84% MAPE and shows the seasonal variation for more than 12 months, the forecasts diverge significantly.

The benefit of the ARIMA-intervention model is not in the its forecasting power, but rather in identifying and measuring the impact and the propagation in the throughput data series caused by different changes.

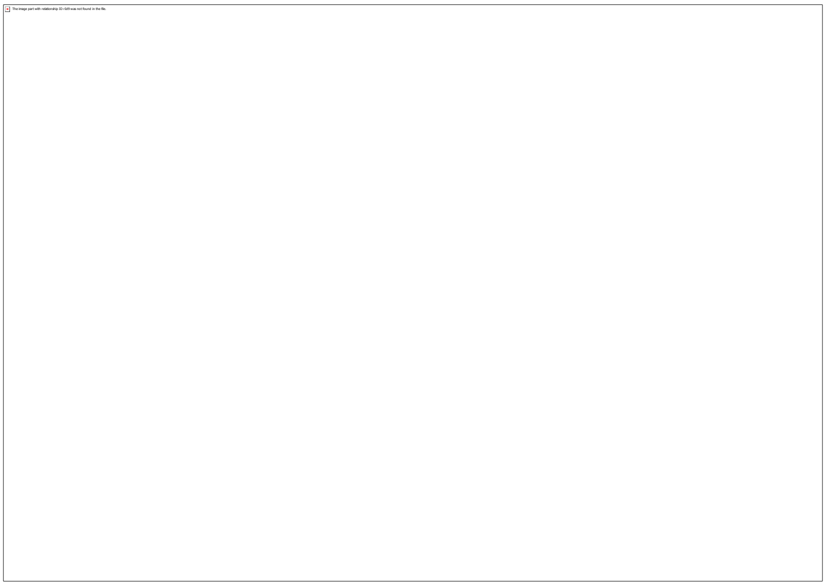

Figure 4: Validation sample (Apr. 2011-Mar. 2015) forecast comparison of different ARIMA models.

Conclusion and Further Research

In this paper, two approaches have been applied to serve three purposes: the first is to generate short-term forecasts, the second is to assess the impact of shocks on the generating process of container throughput and the third is to provide insight into the behaviour of the container throughput of the port of Antwerp. A general purpose of this contribution is to provide a model that can be continuously updated and applied to any port. The model serves to cope with the uncertainty and volatility in demand. Forecasting the number of containers at the port level assists in the planning of the operational decisions such as the port capacity utilisation, loading and unloading planning, handling of container activities and hinterland connections capacity provision.

The seasonal ARIMA outperforms the seasonal ARIMA intervention model wrt forecasting performance. Nonetheless, the advantages of the intervention model are in identifying and quantifying the impact of shocks on the behaviour of the time series and adding to our understanding of the impact of different policy actions. The empirical analysis of the ARIMA intervention model shows that the actual impact of the US financial crisis occurred earlier than the observed fall in the throughput data.

The comparison of the different models showed that the ARIMAX for container throughput as an output series, and the industrial confidence indicator of the Euro Area leading two months as an input series, is more accurate in forecasting, based on the mean absolute percentage error. The results of this study form a starting point for further development and application of causal dynamic models for the long-term forecasting of port cargo flows.

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