A statistical forecasting model applied to container throughput in a multi-port gateway system: the Barcelona-Tarragona-Valencia case.

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Abstract

This contribution investigates the container throughput flow in a multi-port gateway system: Barcelona-Tarragona-Valencia (BTV). First, the paper examines the recent dynamics of the total and transshipment flow showing a relevant shifting of traffic share from Barcelona to Valencia. A novel model based on a two-state Markov model in conjunction with a Monte Carlo experiments is implemented to estimate the predictions of annual growth in container throughput. Verification tests show how the predictions are reasonably good with error metrics similar to other methods based on time-series analysis (trend projections and ARIMA). The strength of the method relies in the statistical nature of the predictions provided (i.e. mean and data dispersion). The method is considered suitable for short-term forecasting. The practical application of the method considers separately the import/export and transshipment container throughput, revealing a different dynamics in both container flows.

Keywords: *Markov Chain, traffic predictions, Monte Carlo method, transshipment*

1. INTRODUCTION

In recent years, predictions of port freight have received increasing attention in ports management and transport logistics. Two different analytical approaches are used to predict port traffic: causal methods and time-series methods. Causal methods involve a high range of geographical and economic variables (for instance, Gross Domestic Product or industrial production projections) for the port traffic forecast (Chou et al., 2008; Lättilä and Hilmola, 2012; Patil and Sahu, 2016). In contrast, time-series prediction methods are based on the projection of a past pattern into the future (Peng and Wu, 2009; Zhang et al., 2013; Twrdy and Batista, 2016). In general, the literature review suggests that time-series analysis methods are performed for short and medium term predictions (less than 5 years) while for long-term predictions causal methods seem more appropriate (Indra et al., 2015). However, some authors use both time-series projections and causal variables for short-term projections (Chou et al., 2008). A third approach of forecasting methods is based on qualitative techniques, where the predictions rely on expert human judgment. These methods are based on iterative strategies, preventing an individual dominant factor (for instance the Delphi method). They are suitable when data are particularly scarce and may be quite effective for long-range forecasting (Indra et al., 2015). Complementing qualitative methods, hybrid techniques have been developed, including qualitative and analytical analyses with a good level of prediction accuracy (e.g. Duru et al., 2012; de Lange et al., 2012). In the main, as noted by Twrdy and Batista (2016) or Peng and Chou (2009), there is not a clear best method for realistic predictions in container throughput. Uncertainty of container flow predictions is related with regional and global economic evolution, trends in world maritime transport, the limitations of mathematical models, or the private-sector economic strategies of terminal operators and shipping lines, among other factors. Despite the uncertainty of the forecasting models, their results in terms of freight demand are used for port planning and development (see examples in Indra et al., 2015).

Focusing on prediction methods based on time-series, some of the most commonly used are trend projection models, Grey theory based models and the Box–Jenkins models. These models have been compared in port traffic forecasting (e.g. Peng and Chou, 2009; Twrdy and Batista, 2016; Indra et al., 2015). Regression or trend projection models are the classical models where a polynomial regression is fitted according to the observed data. Grey models are based on Grey system theory (Deng, 1989),

which has the ability to describe systems with unknown parameters. From the simplest point of view, Grey system based predictions can be viewed as curve fitting approaches (Kayacan et al., 2010). Box–Jenkins based predictions apply a systematic method based on three stages: to identify the appropriate model, to develop a parameter estimation and a final checking to test the suitability of the model. A very widely used model based on the Box–Jenkins approach is the ARIMA (Auto-Regressive Integrated Moving Average) model described in Box et al. (2008).

In recent years Mediterranean ports have been the focus of intensive investigation (e.g. Gouvernal et al., 2005; Medda and Carbonaro, 2007; Notteboom, 2010, Twrdy and Batista, 2016). The geographical location of the Mediterranean Sea, within the East-West maritime traffic via the Suez Canal, prompted the development of hub ports and multi-port gateways capturing traffic heading towards the north of Europe (Notteboom and de Langen, 2015). Focused on container throughput, an alternative to individual port analyses led to the concept of multi-port gateway regions. In this case, under criteria such as similar hinterland, competitive relations among ports or the calling patterns of the shipping lines, the ports are grouped together under a regional geographic denomination (Notteboom, 1997 and 2010). The definition of multi-port gateway systems makes it possible to explore and compare the regional dynamics, intra-port competition, historical trends, predictions and developments of the container throughput. One of these multi-port gateway regions is formed by the southern European system of the ports of Barcelona-Tarragona-Valencia (BTV), also called "Spanish Med Range". BTV container throughput was ranked in fourth position in the European container port system by Notteboom (2010) using data from 2008. The BTV inland corridor extends to the Madrid area and the South of France, with a logistic core region complementing a highly diversified industrial activity (Figure 1). Initiatives from the port authorities have been oriented towards developing inland terminals to penetrate into regional markets (Van den Berg and De Langen, 2011; Van den Berg et al., 2012). Barcelona and Valencia are among the largest Mediterranean ports, with relatively well-balanced transshipment and import–export activities (for instance, the transshipment activity was 38.8% and 43.9% in Barcelona and Valencia respectively during 2015).

The objective of this contribution is to implement and analyse the results provided by a statistical method for container throughput. From a methodological point of view, we present a new methodology that conjugates the Markov Chain and the Monte Carlo simulations in the framework of methods based on time–series analysis. The method is applied in the container throughput development of the BTV multi-port gateway system. Thus, as a first step, the investigation examines the container dynamics of the BTV system at regional scale. In consequence, the practical view developed in this contribution supports the "multi-port gateway regions" as a unit of analysis in the European container port system introduced by Notteboom (2010). Despite the relevance of the traffic share of Algeciras bay port in the Spanish system, this is not included in the analysis because it focuses on transshipment activity and it does not shear the same hinterland (Notteboom's criteria).

This contribution is organized as follows: after the Introduction (Section 1), a description of the BTV port system in terms of container throughput is presented in Section 2. Section 3 describes the prediction model from a methodological point of view. Then, Section 4 shows the results of the application of the method at the BTV port system. A set of verification tests with historical data and a comparison with other investigations and state-of-the-art methods are presented in Section 5. A discussion of the results obtained is presented in Section 6. Finally, the main conclusions and future works are highlighted (Section 7).

2. BTV PORT SYSTEM DESCRIPTION

In terms of container flow, the BTV multi-port system feeds from the east–west Mediterranean route in the framework of container transshipment and import/export activity from its hinterland. The main

hinterland served by BTV covers Spain and the south of France. In the European context, the BTV multi-port system has benefited from an extension of its hinterland with the advantage of offering a lower transit time in comparison to northern range ports to accommodate Far East cargo flows (Notteboom, 2010). A critical point of the BTV multi-port system is the difficulty in establishing rail shuttles to connect to North European areas due to the difference in rail gauge, which limits the expansion of logistic corridors (Gouvernal et al., 2005).

The BTV container throughput increased from 70,874 TEU in 1973 to 6,670,298 TEU in 2015 following the global trend towards containerisation (Figure 2.a). From an historical point of view, both Barcelona and Valencia covered the whole of the BTV container throughput with a similar traffic share. However, since 2006 a turning point in traffic flow in Barcelona has led to a noticeable increase of the traffic share at Valencia Port (Figure 2.b). Among other reasons for this, Valencia Port was selected in 2002 as a Mediterranean hub by the shipping company MSC, leading to a percentage of transshipment over 50% after 2009 (see the next paragraph). However, the traffic relationship between Barcelona and Valencia is more complex: the annual growth rate (Figure 2.c) does not present a negative significant correlation (r=0.81, p<0.001 for the period 1973–2015). The level of concentration of the BTV multi-port system is evaluated following the Hirschman–Herfindahl index (HH) which is computed in Equation 1.

$$HH = \frac{\sum_{i=1}^{n} TEU_i^2}{\left(\sum_{i=1}^{n} TEU_i\right)^2} \tag{1}$$

where i to n is the number of ports in the port system. When HH approximates to 1, this means that the total traffic flow is dominated by one specific container port. On the other hand, when HH tends to $1/n$ the traffic flow is spread widely among the ports. Figure 2.d shows HH computed for the BTV port system. From an historical point of view, the index HH has evolved from below 0.4 during the first year with data available (1973) to 0.55 in 2015. This evolution was characterized by a first period, when the traffic shear was controlled by Barcelona Port (late 1970s with HH>0.5), followed by a relatively constant HH period (below 0.5) during the 1980, 1990 and 2000, where Barcelona and Valencia had a similar traffic shear. In the last few years, the index HH has increased significantly due to the increasing leadership of Valencia in container throughput.

The transshipment of containers at terminals and the emergence of "hub" ports induce the requirement to examine the BTV port system considering the import/export (or the transshipment) container throughput. Figure 3.a shows the total container throughput flow and the import/export flow, and Figure 3.b shows the percentage of the transshipment throughput for the BTV ports. During the period 2007–2015, a visual inspection shows a relationship between the increasing percentage of transshipment in Valencia versus the decreasing percentage in Barcelona (+20% versus -25% respectively). The import/export container throughput shows how this activity has remained approximately constant over time in the BTV system. The exceptional increase of container throughput during 2006, 2007 and 2008 at Valencia Port is mainly associated with the transshipment activity (see Figure 3). Considering that the noticeable decrease of container flow occured during 2008 Barcelona relates to transshipment activity, it seems feasible to assume that Valencia Port captured part of the transshipment activity from Barcelona Port. Figure 3.b confirms this trend: an increase of the percentage of the transshipment in Valencia fits with the decrease of the transshipment activity in Barcelona. Historically, Tarragona Port has been focussed on solid and liquid bulk associated with the petrochemical industry in its immediate area of influence. Recently, DPW established a new container terminal with a slight increase of the container throughput (Figure 2).

Although total container throughput information is available from 1973, transshipment information has only been recorded since 2005. In consequence, only 11 years of data are used for the container

throughput predictions. The container throughput data are obtained from the Spanish Port Agency (*Puertos del Estado*).

3. METHODOLOGY

The model used to investigate the container throughput forecasting is based on a two-state Markov model chain combined with a Monte Carlo experiments model. The simple two-state Markov model, applied recently by Twrdy and Batisita (2016) in container throughput analysis, provides information about the dynamics of a port-system container flow considering that the next state of annual growth depends only on the current state and not on the sequence of events that preceded it (memorylessness or Markov property). This means that given a positive integer n and possible states of annual growth rate $s_1, \ldots, s_{n+1}$ as random variable (X), it occurs that:

$$P(X_{n+1} = s_{n+1} \mid X_1 = s_1, X_2 = s_2, \ldots, X_n = s_n) = P(X_{n+1} = s_{n+1} \mid X_n = s_n) \tag{2}$$

The two-state Markov model chain for the BTV system is presented in Figure 4, where the probability for the sequence of annual growth is obtained from the total and transshipment time–series (see Figure 3.a). In this case, the basic model only considers two time-independent states: positive or negative growth. The associated transition matrix, which provides the shift probabilities between both states, is given by:

$$P = \begin{pmatrix} p & 1-p \\ 1-q & q \end{pmatrix} \tag{3}$$

where p is the probability of being positive next year if the current year is positive, and q the probability of being negative the next year if the current year is negative in terms of annual growth. According to the probabilistic data shown in Figure 4, the transition matrix for the total and transshipment container throughput are:

$$P_{total} = \begin{pmatrix} 0.67 & 0.33 \\ 0.33 & 0.67 \end{pmatrix}; P_{transhipment} = \begin{pmatrix} 0.86 & 0.14 \\ 0.50 & 0.50 \end{pmatrix} \tag{4}$$

From the total container flow transition matrix, we can observe how a positive growth in the previous year leads to a 67% probability of there being positive growth next year and 33% of being negative the next year. On the other hand, after negative growth for the past year, the probability of being positive is 67% and the probability of being negative is 33% in the next year (total container flow). The values for the transshipment component are different from the total component flow, indicating a different dynamic between the import/export and the transshipment container flow.

A step forward with the Markov Chain model is to run random simulations following the Monte Carlo method. This method is widely applied for forecasting procedures in other disciplines and provides to the decision-maker with a set of possible outcomes and statistics that will occur in the future. In our case, the purpose of the Monte Carlo experiments is to generate annual growth predictions based on past container throughput patterns (given by a two-state Markov Chain) and then provide statistics for container throughput predictions for the short-term (i.e. 1–3 years). The random nature of the system has been included through a uniform values generator. Combining the probabilities derived from the Markov Chain model, a number of simulations are performed representing different prediction scenarios. The stochastic behaviour in the model was implemented in such a manner that each prediction assumes the two-state Markov Chain model pattern shown in Figure 4. Once the algorithm has determined the sign of the annual growth (positive or negative), the value of the annual

growth is computed with a random value, assuming that they follow a normal distribution with a mean and standard deviation. The mean and the standard deviation have been obtained from the past positive and negative growth separately. The Monte Carlo model has been applied with 20,000 simulations for annual growth forecast scenarios.

Two well-known methodologies are selected to be applied at the BTV multi-port system in order to compare them with the error metrics obtained from the statistical method. These methodologies are based on a regression model with a single independent variable and ARIMA; both of them are appropriate for short-term forecasting (e.g. Peng and Chu, 2009; Indra et al., 2015; Twrdy and Batista, 2016). The simple regression model is formulated as:

$$Y_t = \beta_0 + \beta_1 \cdot t \qquad (5)$$

where β_0 is the intercept and β_1 is the slope of the regression line over time t. Both coefficients are estimated from data using least square method. The ARIMA model is generally denoted as ARIMA *(p,d,q)* where *p, d* and *q* are non-negative integers which define the order of the autoregressive model, the degree of the differencing and the order of the moving-average model respectively. Particularizations of the formulation of ARIMA and its identification procedure parameters are found in Box et al. (2008).

4. RESULTS

The descriptive statistics of the 2016 prediction for the total and transshipment container flow are presented in Table 1. The averaged values (μ) for total and transshipment flows at BTV are 6,927,681 TEU and 3,112,568 TEU with a standard deviation (σ) of 510,672 TEU and 344,093 TEU respectively. As a preliminary verification test, the latest data (June 2016) show a first semester growth of about 4.2% at BTV, which would result in a total TEU flow of nearly 7 million TEUs during 2016, closer to the total flow predicted. The statistical nature of the method makes it possible to obtain additional parameters such as the kurtosis or the skewness. The kurtosis in both cases is below 3, which means that, in the resultant distribution of the predicted traffic, the weight of the tails relative to the rest of the distribution has no noticeable importance (i.e. the relative noticeable concentration of data near the mean). Alternatively, the skewness is small, which means that the solutions provided by the Monte Carlo method have no relevant asymmetry.

Figure 5 shows the time–series for a three-year predictions sequence jointly with the past traffic data. The mean value and the $\mu\pm\sigma$ time–series are also shown. The results for both time–series (total and transshipment flows) show a clear positive tendency predicted in both cases consistent with the past container flow pattern. The results also reveal an increase of the prediction range when the forecasting step (i.e. year predicted) increases; this means that the standard deviation increases when the prediction horizon is increased. This is also observed in the range of values of the histogram distribution for three-year prediction for total container and transshipment flows (Figure 6). The histogram classes (15) are established considering the Sturges rule (Sturges, 1926). For the first year's prediction of the total container flow (i.e. 2016; Figure 6.a), the histogram shows a relatively "non-flattened" and symmetrical distribution consistent with the kurtosis and the skewness values. This pattern is similar in both flows (i.e. total and transshipment container flow) and for the sequence of predictions for 2017 and 2018. According to the visual inspection and the statistical parameters, the predictions seem to follow a normal distribution. For instance, for the 2017 and 2018 predictions, the kurtosis is 2.50 and 2.76 respectively (values near to the 2016 prediction), which are near to the expected values for a normal distribution pattern (i.e. 3). If the predicted container flow follows a normal distribution, it means that 68% of the predictions are in the range $\mu\pm\sigma$ (green lines in Figure 5), and 95% of the predictions are inn the range $\mu\pm2\cdot\sigma$. This information, jointly with the information

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shown in Figure 6 and Table 1, may be relevant for a decision-making framework because the method provides an averaged prediction and additional information on the uncertainty of the prediction. For instance, the cumulative distribution function shown in Figure 6 determines the probability of being higher/lower at a certain traffic flow. This may be relevant for investment planning or handling the assignment of terminals operators in the next year's strategies.

5. VALIDATION TEST AND COMPARISON WITH OTHER METHODS

In this section, a set of numerical tests have been carried out with the purpose of examining the skill assessment of the model. The first test is performed by comparing past year predictions with their corresponding real time–series. For instance, the prediction for 2015 has been carried out using 2005–2014 container flow information. Table 2 shows the "first-year" prediction during 3 consecutive years. The container traffic predicted in 2015 is 6,714,619 TEU, which is close to the real traffic that was 6,670,284 TEUs. In this case, the absolute error was 0.67%. The results for 2014 prediction show similar results: the absolute error is 2.01%. In both cases, the solution is in the range μ±σ predicted according to the standard deviation shown in Table 2. However, the error in the prediction for the year 2013, increases reaching an absolute error of 13.96%. This is due to the noticeable decrease of container activity during 2013, opposed to the historical positive tendency. This prediction test confirms the impossibility of the statistical method capturing turning points from a global tendency in a similar way to other methods based on time–series analysis (Indra et al., 2015).

A complementary validation is carried out by analysing the three-year container forecast (2014, 2015 and 2016) using 2013 as the base year. The container flow value for 2016 has been extrapolated linearly from the accumulated traffic data at August 2016 (last data available). In this case, the skill assessment of the model has been computed using the following error metrics: Root Mean Square Error (RMSE), the Mean Absolute Error (MAE) and the Mean Absolute Percent Error (MAPE):

$$MAE = \frac{\sum_{t=1}^{n}|Y_t - \hat{Y}_t|}{n} \tag{6}$$

$$MAPE = \frac{100 \cdot \sum_{t=1}^{n}\left|\frac{Y_t - \hat{Y}_t}{Y_t}\right|}{n} \tag{7}$$

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(Y_t - \hat{Y}_t)^2}{n}} \tag{8}$$

where $\hat{Y}_t$ is the measured container throughput and Y_t is the predicted container throughput over time t. The container throughput results for the three-year predictions are shown in Table 3, jointly with the evolution of the standard deviation and error metrics presented previously. The container flow prediction has a reasonable agreement for the three years: in all cases the real container flow falls in the range μ±σ with a MAPE of 2.2%. The MAE and RMSE are below 160,000 TEUs, approximately 2.5% of the total flow. In this sense, the results shown in Table 2 and 3 reveal a percent error in similar terms to the results shown in Peng and Chu (2009), which compare six univariate models for container forecasting applied at Taiwan's three major ports. Peng and Chu (2009) obtained a MAPE with a range of 2.15% (classical decomposition method) and 7.10% (Hybrid Grey method); however, the comparison with our results is not fully conclusive because Peng and Chu (2009) used very short–term predictions (i.e. monthly) with a consequent difference in the volatility dynamics such as the seasonal pattern. Using year predictions, Twrdy and Batista (2016) applied the quadratic trend model with a mean absolute percent error between 2.9% and 5.5%; this means similar error metrics to the statistical method presented in this contribution. Other examples of port throughput predictions with

similar error metrics are found in Zhang et al. (2013), Patil and Sahu (2016) and Hui et al. (2004). However, as mentioned previously, the standard deviation shown in Table 3 increases in relation to the year predicted. This suggests the suitability of the method for short-term forecasting (i.e. 1–3 years): longer predictions would increase the standard deviation (larger dispersion of the simulations), approaching the magnitude of the mean. The effect on the quality of the solution to the year horizon prediction is considered as a future work. Also, the length of the historical years used to compute the transient matrix, which is the core of the method presented here, is an issue to be considered in further investigations.

The experiment using as a base year 2013 is replicated using the simple linear regression model and the non-seasonal ARIMA models: ARIMA (0,1,0), ARIMA (1,1,0) and ARIMA (0,1,1). One order of differencing ($d=1$) is chosen due to the non-stationary pattern identified in the original time-series (Box et al., 2008). ARIMA(0,1,0) represents a random walk model and is formulated as:

$$Y_t = \mu + Y_{t-1} \tag{9}$$

where the constant term (μ) is the average period-to-period change in the data (i.e. long term drift). The constant term is included because the model selected has one order of differencing and the time–series has a non-zero average. ARIMA(1,1,0) represents the differenced first order autoregressive model:

$$Y_i = \mu + Y_{i-1} + \theta(Y_{i-1} - Y_{i-2}) \tag{10}$$

where θ is the slope coefficient. ARIMA(0,1,1) is a simple exponential smoothing with one order of differencing:

$$Y_i = \mu + Y_{i-1} + \alpha e_{i-1} \tag{11}$$

Table 4 shows the error metrics for the simple regression method and the ARIMA models for the forecasting experiment in which 2013 was taken as the base year. So, these results are compared with the error metrics shown in Table 3. The linear regression model shows larger errors than the statistical method. For instance, MAPE is 2.22% for the statistical method against 6.10% for the linear regression method. Compared with ARIMA models, the statistical method shows similar error metrics. For instance, differences of ~20.000 TEU are obtained when comparing the RMSE obtained from ARIMA(0,1,0) or ARIMA(1,1,0) and the statistical method (123,540 TEU, 137,142 TEU and 159,747 TEU respectively). Although there is not a best forecasting model (Peng and Chu, 2009; Twrdy and Batista, 2016), the statistical method presented here showed a reasonable agreement with the container data flow, with similar error metrics to other state-of-the-art methods. However, further research and more inter-comparison exercises are suggested to assess the reliability of the statistical method based on two-state Markov model with the conjunction of Monte Carlo experiments.

6. DISCUSSION

This investigation has shown the rapid increase of the container throughput during the period 2000–2015 for the BTV system. The shipping and terminal companies' decisions have affected the container traffic share among the ports of the BTV multi-port system: Valencia nowadays has a relevant role in the world transshipment market and Barcelona is specialized in the import/export market, with a good geographical position to increase its hinterland towards the north (Van den Berg et al., 2012). This is confirmed by the analysis shown in the previous sections, where a significant correlation in the transshipment flows between Valencia and Barcelona was found. The position of marine routes and the relevant production region makes it valid to consider the BTV multi-port system as being in an optimal position in the European and Mediterranean markets.

Port competitiveness in the BTV multi-port system will be relevant in the future with the increase of north–south rail network connection or new patterns in world maritime traffic. In this sense, port traffic forecasting models are nowadays the focus of investigation: planners and port managers seek the ability of forecast models for appropriate decision-making. The mentioned relevance of private agents in the intra-port traffic share limits the prediction skill for the container flow for the BTV ports, but considering them as a unique entity, the predictions present good results according to the verification tests. This fact supports the multi-gate system definition mentioned previously (Notteboom, 2010).

The statistical method, based on two-state Markov model with the conjunction of Monte Carlo experiments, presented in this contribution captures the trend, but presents difficulties in predicting turning points or outliers. This disadvantage is common in other forecasting methods based on time–series analysis (Indra et al., 2015). This is because these methods are based on the principle by which the pattern of the past is reproduced in the future. For instance, the turning point for year 2013 was not captured by the statistical model according to the verification tests shown previously. Also, the evolution of the transshipment market is highly influenced by shipping companies' decisions (for instance, the selection of Valencia as a hub port by MSC), which may represent a disruption that the forecasting model does not capture. These disadvantages are common in other time–series–based models where the past behaviour is maintained in the future (*e.g.* ARIMA models). However, they are a competitive tool for new infrastructure construction and maintenance, and for operation management, such as the assignment and acquisition of handling equipment (Indra et al., 2015).

One of the advantages of the statistical model presented here is that the set of forecasting results is provided in terms of statistical outcomes (for instance, histograms or cumulative plots). In this sense, the range of probability of traffic growth provided by the statistical method suggests inputs for a final decision to be taken by port planners and managers. Therefore, qualitative techniques that rely on the expertise of human judgment may complement the final estimation (de Lange et al., 2012; Duru et al., 2012). The qualitative methods are also suitable when ambiguous or incomplete data are available, or disruptive factors are present. In consequence, the statistical method presented in this contribution is a good complement for qualitative forecasting methods (e.g. the delphi method) due to the statistical outputs. The qualitative methods have been applied previously in maritime volume forecasting by Duru et al. (2012), de Lange et al. (2012) and Rashed et al. (2015), highlighting the ability of these methods to predict shipping industry trends and capture turning points in the time–series.

A Markov Chain is a stochastic process, but it differs from a general stochastic process in that a Markov Chain must be "memoryless". This means that the transition from one state to another does not depend on how the variable (in our case growth) arrived at this present state (Markov property). In the container growth rate, the Markov property may be assumed according to the time–series data; in this case, the container predictions are based on the transition matrix P as a unique source of information. The integration of the past information through the transition matrix led to a high dependence of the method on a relatively small amount of information. In consequence, seasonal or cyclic patterns are not included in the statistical method, by contrast with to classical decomposition methods or Seasonal-ARIMA models (see the comparative analysis in Peng and Chu, 2009). However, according to our results, the application of the statistical model may provide feasible solutions with a relatively limited set of observations. This may differ from other time–series methods; for instance, ARIMA models suggest more than 50 observations (Indra et al., 2015). The number of observations used in our predictions was 10 years of data. This length is similar to other traffic predictions based on time–series analysis (for instance, Farhan and Ping Ong, 2016). Although container information in the BTV multi-port system is available from 1973, the 1970s, '80s and '90s decades haves not been included in the analysis because these include the boom of the

containerization boom; in this case an overestimation of the total container prediction was observed if these decades were considered (results not shown).

The application of the statistical method including the transshipment flow leads to predictions with more dispersion due to the volatility of the transshipment market. An example is the application of the statistical method for Barcelona and Valencia flows separately (Figure 7). The predicted container flows show how the deviation of transshipment flows from Barcelona to Valencia (which occurred mainly during 2008 as noted previously) has a relevant impact on the Barcelona flow prediction. A Zero growth predicted in this port is likely due to the turning point that occurred in 2008 (see Figure 3.a); a positive tendency would be more reliable according to the positive annual growth of 2014 and 2015 after the transshipment flow has been "readjusted". Also, the effect of the establishment of the DPW terminal at Tarragona Port may be another source of disruption in future predictions in the event of a significant increase of the container flow at this terminal.

7. CONCLUSIONS AND FUTURE WORKS

This contribution has addressed the dynamics of the container flow in the multi-port gateway system of Barcelona-Tarragona-Valencia. The examination of the container dynamics in this port-system has revealed a significant evolution of the relative weight among the three ports. The statistical method implemented focuses on annual growth of container forecast and is based on two-state Markov Chain and Monte Carlo experiments. The method has an acceptable level of agreement with real data according to verification tests. The comparison with other state-of-the-art methods reveals the suitability of the method for port traffic forecasting. One of the advantages of the method in comparison to other univariate methods is to provide statistical outcomes (e.g. histogram, cumulative probability function, etc.). The probabilistic approach introduces an alternative insight in comparison to conventional quantitative methods and can also be a complement to qualitative methods. According to our results, the more volatile transshipment market leads to a source of disruption in the container throughput predictions. Several future works are planned to analyse the application of the statistical method in other port or multi-port systems, in additional traffic contexts (e.g. transshipment oriented ports), or using different number of observations.

Similar to the neural network or Box-Jenkins methods, the reliability of the models decreases with the increase of the prediction horizon (Lam et al., 2004; Box et al., 2008). In this sense, the sensitivity of the statistical method in terms of the number of observations (meanings its influence on the transition matrix) and the application at different port systems is undoubtedly a further analysis to be addressed. The statistical method is based on a simple two-state Markov-Chain but the application to more complex diagrams may be useful to capture complex patterns or port throughput correlations (similar to the negative correlation for the transshipment flow observed between Barcelona and Valencia). Finally, the normal distribution fitting assumed in the annual growth distribution must also be discussed in future works using a longer period of container flow data. However, the fitting of other distributions in terms of annual growth (for instance, negative distribution) does not modify the methodology significantly.

Figures
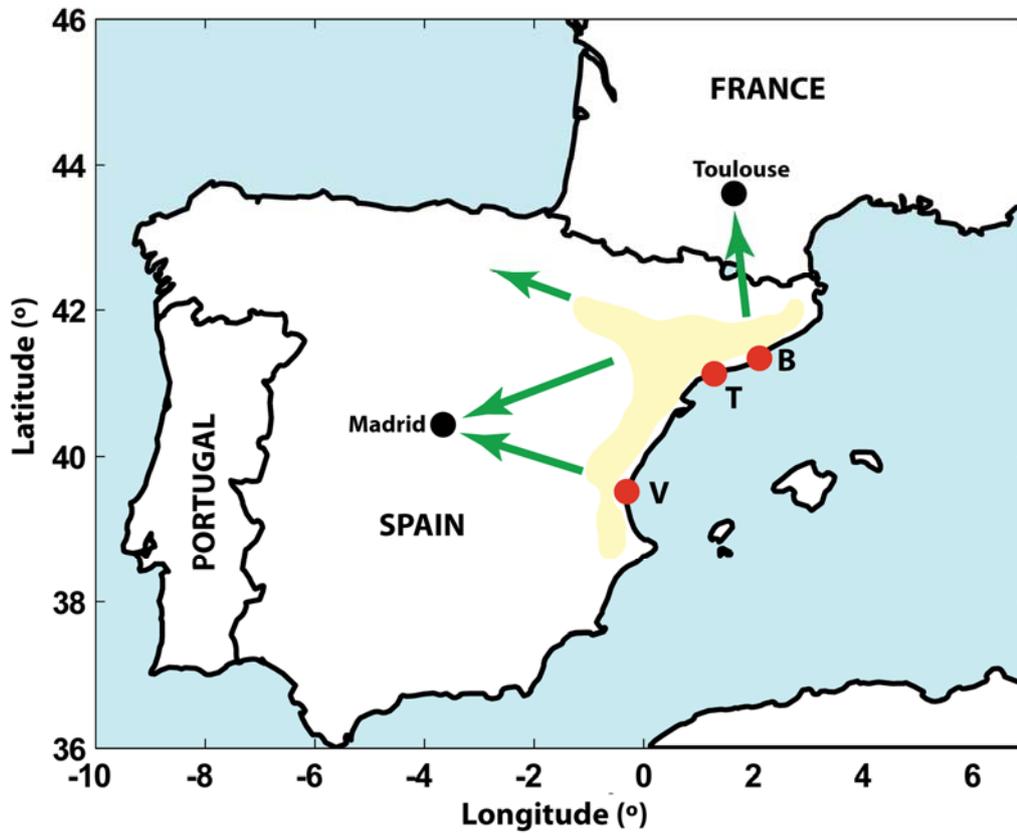
Figure 1. BTV geographical location. Red points are the BTV port locations: B (Barcelona), T (Tarragona) and V (Valencia). Inland corridors are shown by green arrows and the BTV logistic core region is coloured in yellow. Source: adapted from Notteboom (2010) and Van den Berg et al. (2013).
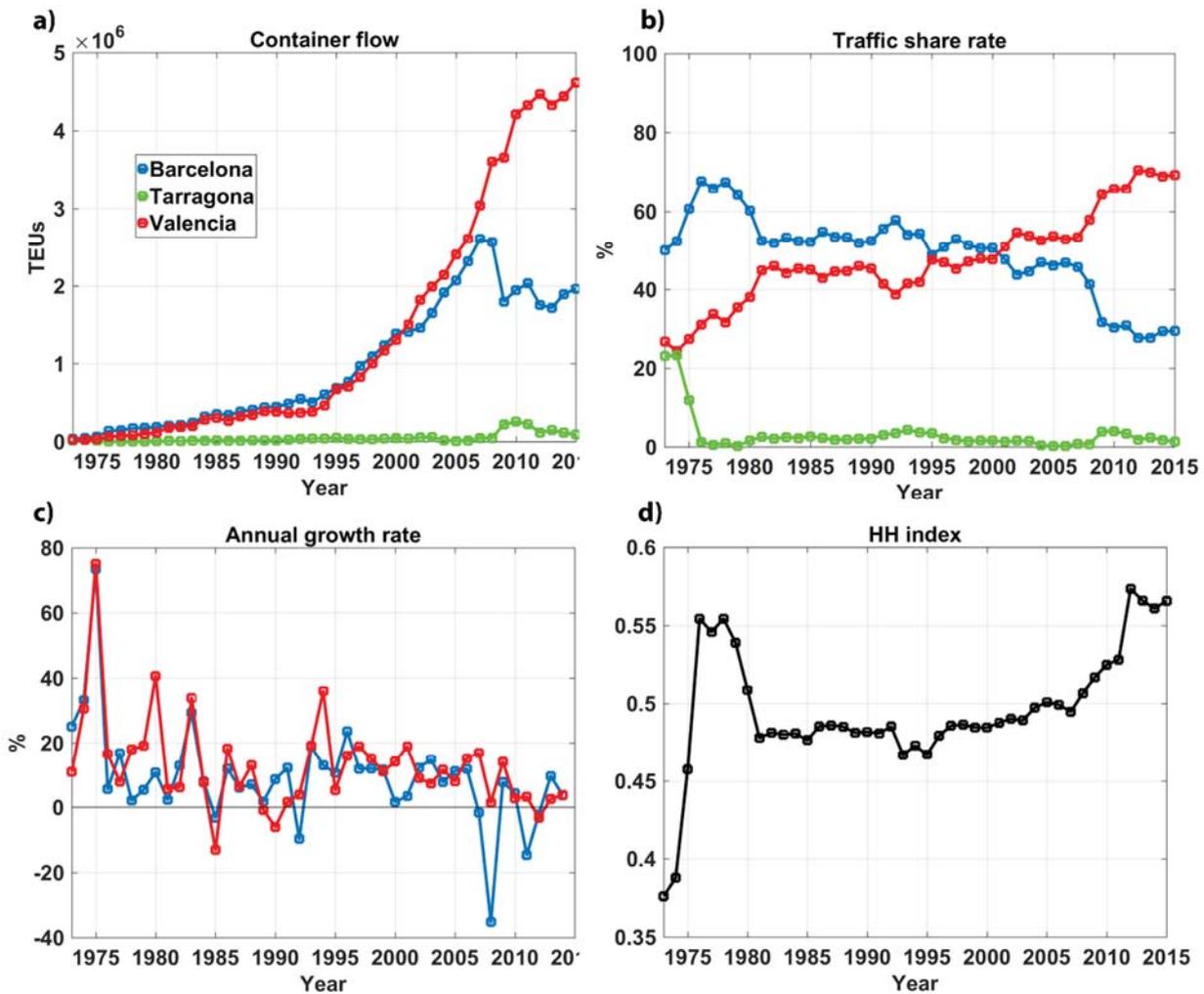
Figure 2. (a) Historical container throughput for the BTV ports. Source: Puertos del Estado (Spanish Port Agency). (b) Traffic share rate for BTV ports. (c) Annual growth rate for Barcelona and Valencia. (d) Hirschman-Herfindahl index (HH).
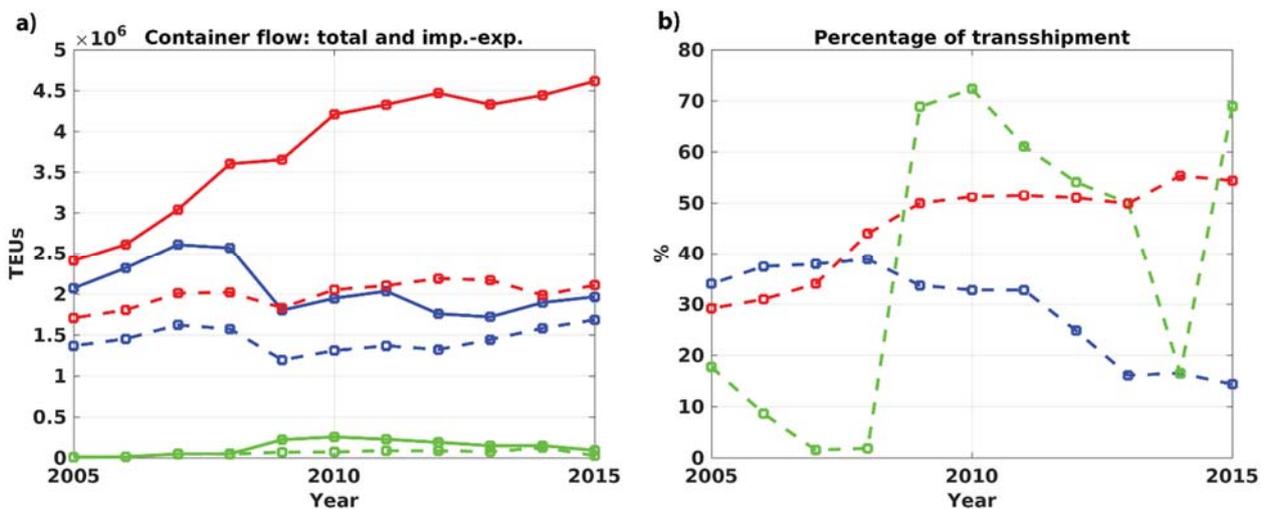
Figure 3. (a) Total (continuous line) and import/export (dashed line) container throughput for the BTV ports. (b) Percentage of the transshipment from the total container throughput. In both figures blue corresponds to Barcelona data, red corresponds to Valencia data and green corresponds to Tarragona data.
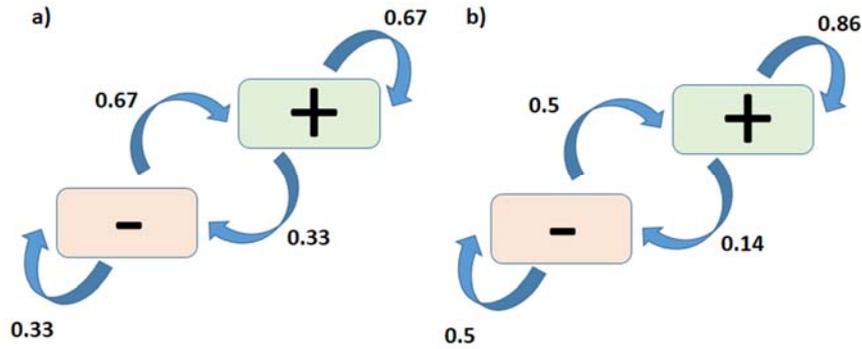
Figure 4. Two-state Markov Chain for the sequence of growth rate, on the left (a) for the total container throughput, on the right (b) for the transshipment container throughput. Numbers indicate probabilities of occurrence of the next year according to the sign of the container growth rate of the previous year.
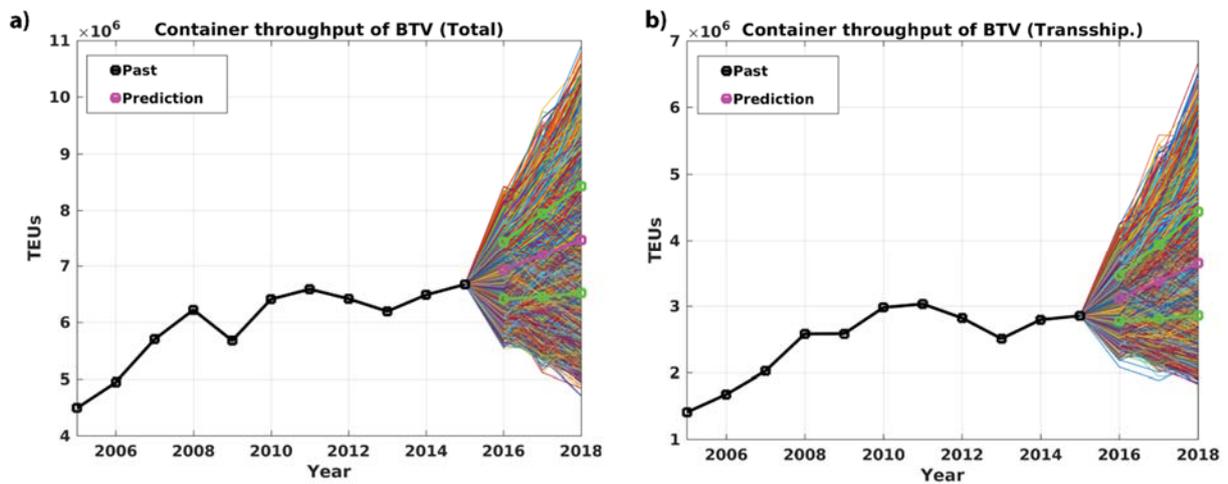

Figure 5. Predictions of the container throughput using Monte Carlo experiments in conjunction with the Markov Chain model. Black bold line is the total container throughput in the BTV systems for the past years. Magenta bold line represents the averaged prediction simulations, green lines represent the range $\mu \pm \sigma$ and the alternative single line colours the different prediction results. On the left (a) the total container throughput and on the right (b) for the transshipment container flow.
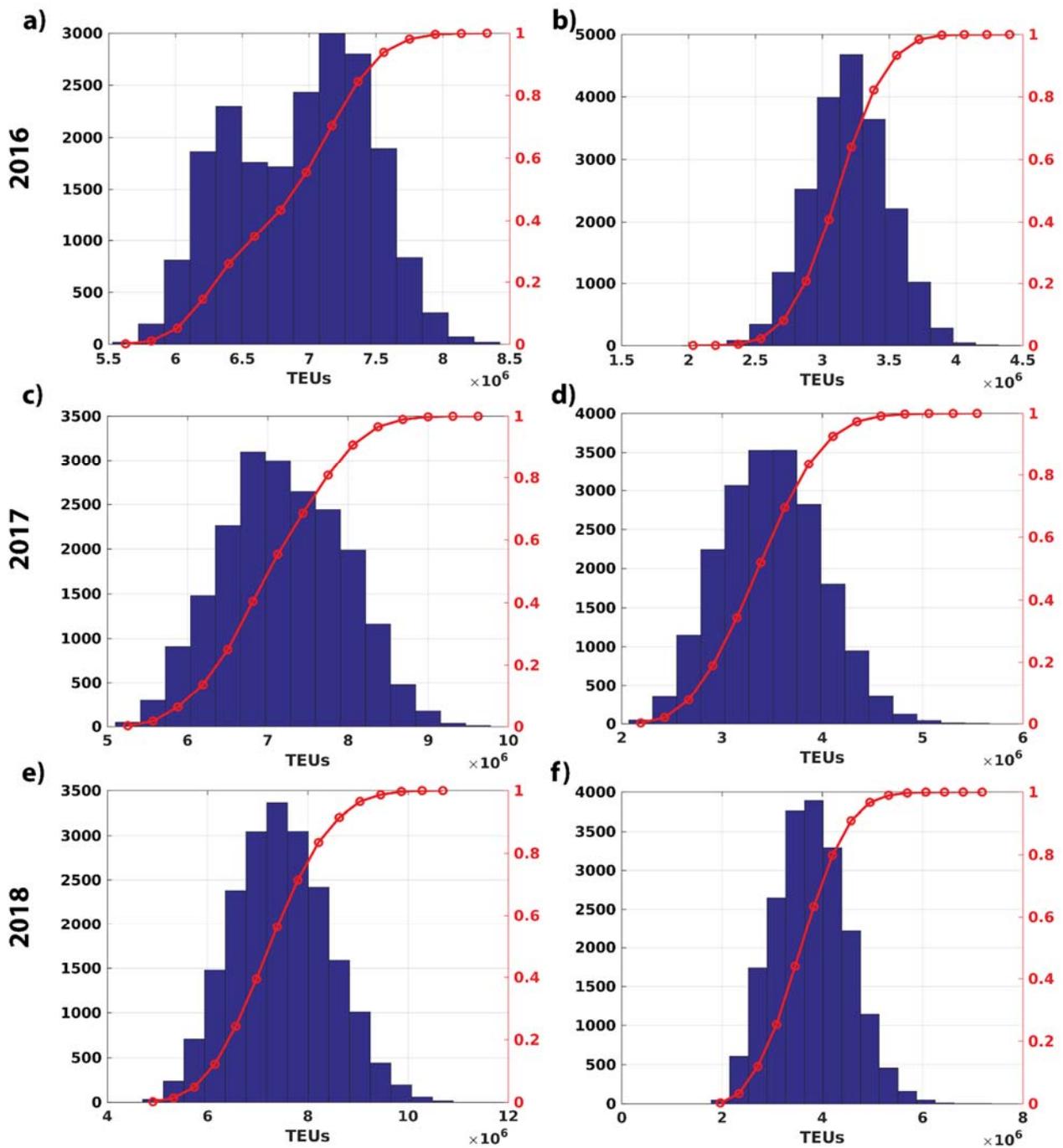
Figure 6. Histogram (in blue) and cumulative probability function (in red) for three-year predictions (predictions 2016-2018). In the left column the results for the total container flow at BTV (a, c, e). In the right column the results only considering the transshipment flow at BTV (b, d, f).
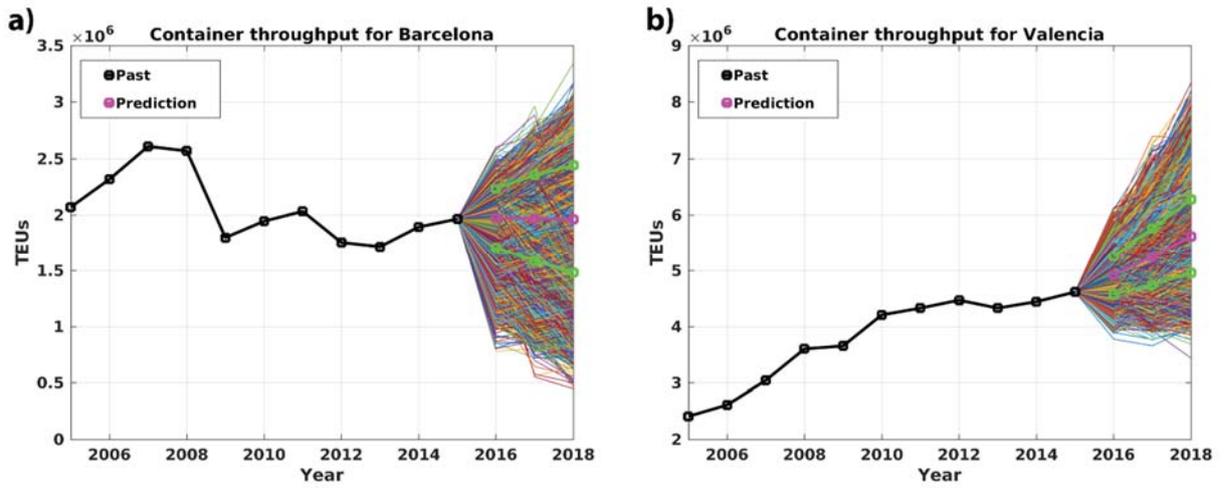
Figure 7. Flow predictions for the total container throughput for Barcelona (a) and Valencia (b) ports. Magenta bold line represents the averaged prediction simulations, green lines represent the range μ±σ and the alternative single line colours the different prediction results.

	Total container flow	Transshipment container flow
Total of prediction simulations	20,000	20,000
Mean (μ)	6,927,681 TEU	3,112,568 TEU
Standard deviation (σ)	510,672 TEU	344,093 TEU
Median	6,997,378 TEU	3,137,626 TEU
Kurtosis	2.10	2.40
Skewness	-0.12	-0.04
Minimum prediction	5,531,098	2,081,986 TEU
Maximum prediction	8,426,835 TEU	4,258,751TEU

Table 1. Descriptive statistics for the 2016 container prediction at the BTV system. Both total and transshipment flows are shown.

Year	Total container traffic (in TEU)	Total container traffic predicted (in TEU)	Standard deviation predicted (in TEU)	Absolute error (in %)
2015	6,670,284	6,714,619	524,913	0.67
2014	6,484,421	6,354,124	528,314	2.01
2013	6,193,863	7,058,625	304,678	13.96

Table 2. Verification test results: real and prediction of the container traffic per year.

Base year 2013		
Year prediction	Mean (in TEU)	STD (in TEU)
2016	6,801,580 *7,025,605*	1.026.988
2015	6,573,368 *6,670,284*	795.955
2014	6,354,124 *6,484,421*	528.314
MAE (in TEU)	150,412	
MAPE (%)	2.22	
RMSE (in TEU)	159,747	

Table 3. Three-year prediction from 2013 as the base year. In italics the real container traffic. The value for 2016 has been extrapolated linearly from the accumulated traffic at August 2016 (last data available).

	Linear regression	ARIMA(0,1,0)	ARIMA(1,1,0)	ARIMA(0,1,1)
MAE (in TEU)	408,057	107,012	120,747	318,883
MAPE (%)	6.10	1.57	1.77	4.77
RMSE (in TEU)	411,958	123,540	137,142	324,803

Table 4. Error metrics of different prediction methods for the 2013 base year experiment. The MAE, MAPE and RMSE for the statistical method based on a two-state Markov model in conjunction with Mote Carlo experiments are shown in Table 3.

References

Box, G.E.P., Jenkins, G.M., Reinsel, G.C., Time–series analysis; forecast and control (fourth edition), 2008, Wiley, pp. 755.

Chou, C. C., Chu, C. W. and Liang, G. S. (2008) 'A modified regression model for forecasting the volumes of Taiwan's import containers', *Mathematical and Computer Modelling*, Vol. 47 No. 9, pp.797-807.

Deng, J.L. (1989), 'Introduction to Grey System Theory', *Journal of Grey System*, Vol. 1, No. 1, 1989, pp.1-24.

Duru O., Bulut E. and Yoshida, S. (2012) 'A fuzzy extended DELPHI method for adjustment of statistical time–series prediction: An empirical study on dry bulk freight market case', *Expert Systems with Applications*, Vol. 39 No.1, pp.840-848.

Farhan, J. and Ping On, G. (2016) 'Forecasting seasonal container throughput at international ports using SARIMA models', *Maritime Economics & Logistics.*

Gouvernal, E., Debrie, J., Slack, B. (2005) 'Dynamics of change in the port system of the western Mediterranean', *Maritime Policy and Management,* Vol. 32 No.2, pp.107–121.

Hui, E. C. M., Seabrooke, W., and Wong G. K. C. (2004) 'Forecasting Cargo Throughput for the Port of Hong Kong: Error Correction Model Approach', *Journal of Urban Planning and Development*, Vol. 130, No. 4. pp. 195-203.

Indra, V., Nottebom, T., Parola, F., Satta, G., Persico, L. (2015) 'Port Traffic Forecasting Tool', Indra et al./D/1.3/DT/2015.06.15

Kayacan E., Ulutas B., Kaynak, O. (2010) 'Grey system theory-based models in time–series prediction', *Expert Systems with Application*, Vol. 37, 1784-1789.

Lam, W.H.K., Asce, M., Ng, P.L.P., Seabrooke, W. and Hui, E.C.M. (2004) 'Forecasts and reliability Analysis of Port Cargo Throughput in Hong Kong', *Journal of urban planning and development*, Vol. 130 No.3, pp.133-144.

de Langen, P.W., van Meijeren, J. and Tavasszy, L.A. (2012) 'Combining Models and Commodity Chain Research for Making Long-Ter Projections of Port Throughput: an Application to the Hamburg-Le Havre Range', *European Journal of Transport and Infrastructure Research*, Vol. 12, No. 3, pp.310-331.

Lättilä, L. and Hilmola, O.P. (2012) 'Forecasting long-term demand of largest Finnish sea ports', *Int. J. Applied Management Science*, Vol. 4, No. 1, pp.52–79.

Medda, F. and Carbonaro, G. (2007) 'Growth of container seaborne traffic in the Mediterranean basin: outlook and policy implications for port development', *Transport Reviews, Vol.27,* No.5, pp.573–587.

Notteboom, T.E. (1997) 'Concentration and load centre development in the European container port system', *J. Transp. Geogr.,* Vol. 5, pp.99–115.

Notteboom, T.E. (2010) 'Concentration and the formation of multi-port gateway regions in the European container port system: an update', *J. Transp. Geogr.,* Vol. 18, pp.567–583.

Notteboom, T.E. and de Langen, P.W. (2015) 'Container Port Competition in Europe', in Lee, C.-Y and Meng, Q. (Eds.) *Handbook of Ocean Container Transport Logistics. Making Global Supply Chains Effective,* Springer, pp.76-96.

Patil, G.R. and Sahu, P.K. (2016) 'Estimation of Freight Demand at Mumbai Port using Regression and Time–series Models' *KSCE Journal of Civil Engineering,* Vol. 20, No. 5, pp.2022-2032.

Peng, W.-Y., Chu, C.-W. (2009) 'A comparison of univariate methods for forecasting container throughput volumes', *Mathematical and Computer Modelling*, Vol. 50, pp.1045-1057.

Rashed, Y., Meersman, H., Sys, C., Van de Voorde, E. and Vanelslander, T. (2015) 'Scenario-based forecasting of container throughput: A conceptual framework', *IAME Conference*, Kuala Lumpur, Malaysia.

Twrdy, E. and Batista, M. (2016) 'Modeling of container throughput in Northern Adriatic ports over the period 1990–2013', *Journal of Transport Geography*, Vol. 52, pp.131-142.

Van den Berg, R., De Langen, P.W. and Rúa C. (2012) 'The role of port authorities in new intermodal service development; the case of Barcelona Port Authority', *Research in Transportation Business & Management,* Vol. 5, pp.78-84.

Van den Berg, R. and De Langen, P.W. (2011) 'Hinterland strategies of port authorities: A case study of the port of Barcelona', *Research in Transportation Economics,* Vol. 33, pp.6-14.

Zhang, C., Huang, L. and Zhao, Z. (2013) 'Research on combination forecast of port cargo throughput based on time–series and causality analysis', *Journal of Industrial Engineering and Management*, Vol. 6 Num. 1, pp. 124-134.