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The Impact of Seasonal Demand Fluctuations on Service Network Design of Container Feeder Lines

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Feeder service network design, container shipping, forecasting, simulation, liner shipping, artificial neural network, seasonality.

ABSTRACT

Customer demand in global supply networks is highly uncertain due to unexpected global and local economic conditions and, in addition, affected by seasonal demand fluctuations for final products. Therefore, the design of shipping services for containerized goods has to prove its economic efficiency under varying conditions of transportation demand. Since liner shipping involves significant capital investments and huge daily operating costs, the appropriate design of the service network is crucial for the profitability of the container feeder lines. Usually, quantitative models used for shipping network design are based on deterministic forecasts, which are prone to errors caused by uncertainty factors and structural changes in the development of demand. This study puts special emphasis on the impact of seasonal demand fluctuations on the structure of the related service networks, the capacity of the fleet operating within the network, the deployment of ship types as well as on the associated routes of the ships. A simulation and artificial neural network based forecasting framework is developed to support the design of service networks of feeder shipping lines. The proposed methodology has been tested for a feeder shipping service in the East Mediterranean and Black Sea region. Numerical results show that seasonal demand fluctuations have vital impact on the network design of feeder lines.

Mevsimsel Talep Dalgalanmalarının Besleyici Konteynır Hatlarının Servis Ağı Tasarımındaki Etkisi

Anahtar Kelimeler:
Besleyici servis ağı tasarımı, konteynır taşıma, tahminleme, benzetim, düzenli hat denizyolu taşımacılığı, yapay sinir ağları, mevsimsellik.

ÖZ

Küresel tedarik ağlarındaki müşteri talebi beklenmedik küresel ve yerel ekonomik krizlerden dolayı oldukça belirsiz olup son ürünlerdeki mevsimsel talep dalgalanmalarından etkilenmektedir. Bu nedenle konteynır yükleri için denizyolu taşımacılığı servis tasarımları, değişen nakliye talepleri altında ekonomik etkinliklerini ortaya koymak zorundadırlar. Düzenli hat deniz yolu taşımacılığı önemli bir sermaye yatırımı içerdiğinden uygun servis ağı tasarımı besleyici konteynır hatlarının karlılığı için çok önemlidir. Genellikle denizyolu taşımacılığı ağ tasarımı için kullanılan sayısal modeller, belirsizlik faktörleri ve talebin gelişimindeki yapısal değişiklikler nedeni ile hatalara neden olabilen deterministik tahminlemelere dayanmaktadır. Bu çalışma mevsimsel talep dalgalarının ilgili servis ağlarının yapısındaki etkisi, ağ içerisinde operasyon gösteren filonun kapasitesi, gemi tiplerinin açılımıyla birlikte gemilerin ilişkilendikleri rotaların belirlenmesine de özel vurgu yapmaktadır. Çalışmada, denizyolu taşımacılığı servis ağlarının tasarlanmasına destek sağlamak için bir benzetim ve yapay sinir ağı temelli tahminleme yapısı besleyici tasarlanmıştır. Önerilen yöntem doğu Akdeniz ve Karadeniz havzasındaki bir besleyici denizyolu taşımacılığı servisi için test edilmiştir. Sayısal sonuçlar mevsimsel talep dalgalanmalarının besleyici hatların servis tasarımları üzerinde hayati öneme sahip olduğunu göstermektedir

1. INTRODUCTION

In the early years of containerization, a deep-sea containership was calling a relatively large number of various-sized ports (multi-port calling). Later the evolution of mega-sized containerships enabled significantly lower transportation costs over long distances. However, by visiting a number of regional ports, mega ships are not operated efficiently. Therefore, as an alternative to multi-port calling systems, hub & spoke (H&S) transportation networks were introduced. In H&S networks, large-sized containerships serve the hub ports and smaller sized feeder containerships provide services between the hub port and the regional feeder ports. In this way, large containerships do not waste sailing time by visiting small-sized ports with low demand, but concentrate on long-haul intercontinental lines. Therefore, regional feeder containership service has received a crucial position in the global H&S networks of shipping lines. According to Ducruet and Notteboom (2012b) about 80 % of worldwide vessel traffic occurs at distances of up to 500 km and more than one half at distances of 100 km. These figures clearly highlight the importance of feeder service.

As an example, one of the Asia-Europe routes of Orient Overseas Container Line (OOCL)'s container service is shown in Figure 1. OOCL based in Hong Kong is one of the world's largest shipping lines providing container services between all continents. Two of their major European destinations are Bremerhaven and Hamburg in Germany from where regional feeder services are provided into the Baltic Sea connecting several regional ports in different countries to the hub ports in Bremerhaven and Hamburg (see Figure 2). Similar H&S systems can be found in other parts of the world, e.g. in Asia with Singapore as hub port or in the Mediterranean with Port Said as hub for servicing spokes in the East Mediterranean and Black Sea region.

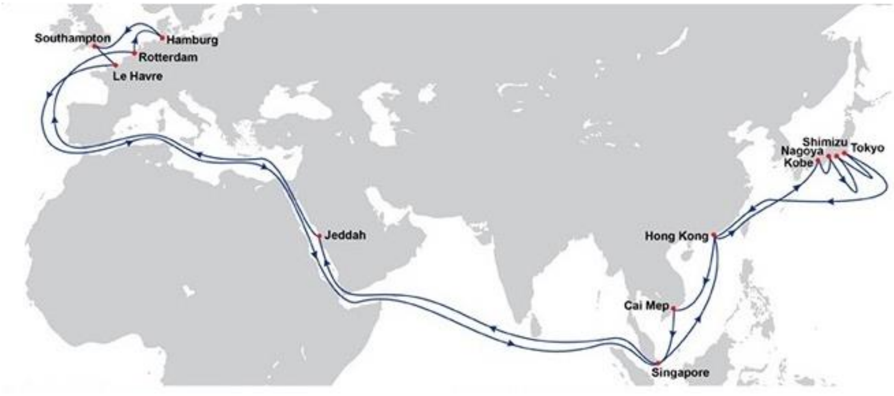

Figure 1. One of OOCL's Asia-Europe container routes serviced by mega containerships (OOCL 2015a)

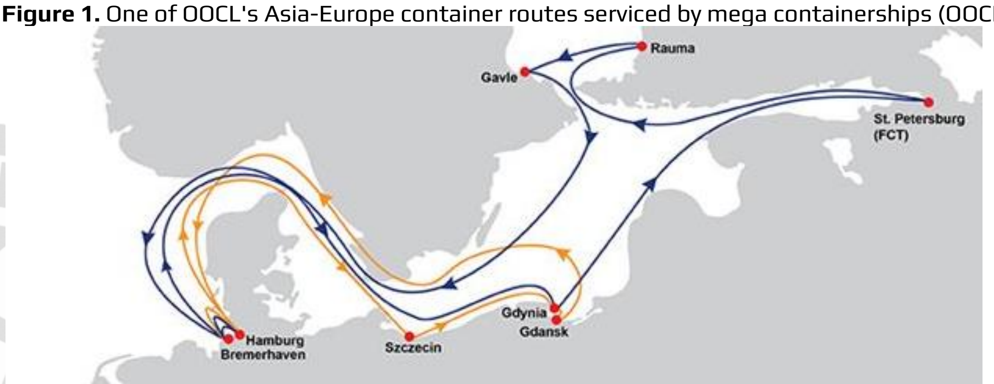

Figure 2. Two of OOCL's feeder service routes with Bremerhaven and Hamburg as hub ports (OOCL 2015b)

The links between the hub port and the regional ports are typically operated as cyclic line bundling service, which simultaneously collect/distribute containers from/to specific regions with small or medium-sized feeder ships. Theoretically, a feeder ship could carry up to twice of its slot capacity in a cyclic route. In this case the ship departs from the hub port fully loaded with import containers, delivers the import containers to the regional feeder ports, simultaneously picks up an equivalent amount of export containers from there, and arrives back at the hub port fully laden with export containers. However, when the trade is imbalanced at the ports, some of the vessel's capacity usually remains idle at the departure or arrival of the ship from/to the hub port. Idle capacity further increases if there is an imbalance of trade in the whole region. As a result, transportation costs per container and total revenue of the shipping line depend of the utilization of the fleet of ships.

Liner shipping requires high capital investment resulting in huge fixed costs for the entire fleet of containerships. At the same time there are considerable variable costs incurred for the operation of the vessels. The return on these investments depends on the transported container volume and the utilization of the vessels' capacity. Operational costs for a container line provider include ship related fixed costs and service related variable costs. Table 1 shows the respective basic cost calculations for a sailing season (Polat et al. 2014).

Table 1. Basic calculations of total costs for a sailing season (Polat et al. 2014)

Parameter	**Basic calculation**
Total costs	*Fixed costs + Variable costs*
Fixed costs	*Number of necessary ships ∗ (Chartering + Operating costs)*
Variable costs	*Number of services * (Bunker (sea) + Bunker (port) + Port set up charges)*
Number of required ships	$\lceil$(*Voyage duration + Lay-up duration*) / *Service frequency*$\rceil$
Number of services	$\lceil$*Planning period / Service frequency*$\rceil$
Voyage duration	*On-sea duration + On-port duration (feeder ports) + On-port duration (hub)*
Idle duration	*Number of necessary ships ∗ Service frequency - (Voyage + Lay-up duration)*
Ship total duration	*Voyage duration + Lay-up duration + Idle duration*

Basically, the demand for liner shipping is closely linked to the development of the world economy and world trade (Zachcial and Lemper 2006). In addition, there are close relationships between regional economic developments, which affect the supply of export goods as well as the demand for import goods and raw materials. Therefore, a change in world or regional trade will lead to a change in transportation volume (Lun et al. 2010). Apart from long-term economic trends and conditions faced by the global economy, the demand for container shipping fluctuates due to seasonal factors, peaks at certain times of years, and unexpected sharp drops and cancellations (Meng et al. 2012; Polat and Uslu 2010; Schulze and Prinz 2009). The production and consumption of some goods typically varies over the year, some following harvest seasons like fruit or fish products. In addition, public, national, and religious holidays cause variations in demand. While some of these factors only affect a single port or region, others even create peaks in global trade, like Christmas and Chinese New Year. Another factor that causes demand fluctuations is unexpected local and global economic development, e.g. financial and political crises. In these periods, the global and regional liner shipping industry usually experiences a sharp decline in demand. Hence the demand of the ports is only occasionally steady during a year (Løfstedt et al. 2010).

Consequently, the trade volume arising at ports determines the necessary fleet capacity for a shipping line. Since demand is uncertain, shipping lines must carefully consider their capacity decisions on whether or not to expand it. Postponing the increase of slot capacity entails the risk of shortages when the demand volume is increased (Lun et al. 2010). Essentially, transportation demand is the driving force in the design of the service network. Even small variations of the demand pattern may lead to an entirely different service network design (Andersen 2010).

In this study, a Monte Carlo simulation and artificial neural network based forecasting framework is developed in order to analyze the impact of seasonal demand fluctuations on the feeder service network design. The proposed model implementation is tested for the container feeder service in the East Mediterranean and Black Sea region. The remainder of this study is structured as follows. In the next section, a brief review of the relevant literature with a focus on forecasting container transportation demand and liner network design is given. In Section 3 a forecasting framework is proposed. Section 4 introduces the case study of feeder service in the East Mediterranean and Black Sea region and summarizes detailed numerical results. Finally, conclusions are drawn and suggestions for further research are given in Section 5.

2. RELEVANT LITERATURE

In recent years, maritime liner shipping has become a popular topic of academic research worldwide. A number of papers addresses different planning aspects in this area has been published in recent years. See Ronen (1983; 1993), Notteboom (2004), Christiansen et al. (2013; 2004), Kjeldsen (2011), Hoff et al. (2010), Ducruet and Notteboom (2012a), Yang et al. (2012), Zheng et al. (2015) and Tran and Haasis (2015) for comprehensive reviews on liner shipping. In this study, therefore, we review studies focussing on container throughput forecasting rather than studies related to liner shipping.

Since the mid-1950s, forecasting accurate container throughput demand of ports is one of the major challenges of all port operators (Goulielmos and Kaselimi 2011). Forecasting transport demand for a shipping line in a region with the desired accuracy is nearly impossible. However, this does not mean that forecasting is pointless. The aim of forecasting is to understand the uncertain future developments through exploring the currently available information on historical demand figures. Therefore, forecasting container throughput of ports plays a critical role in decision making of shipping lines. Table 2 summarizes some related studies on container throughput forecasting and highlights the methodologies and case studies used in the related papers. In the published studies, the authors usually present alternative forecasting methods for container feeder lines under a fixed demand pattern without considering seasonal demand fluctuations, which does not reflect the reality of container shipping. Effective service network designs strongly contributes to the overall economic position of the container feeder lines due to considerable capital investments and huge daily operating costs of shipping lines.

Table 2. Container throughput forecasting studies

Authors (Years)	Proposed Methodology	Benchmark methodology	Port/Region
Walter and Younger (1988)	Iterative Nonlinear Programming		New design
de Gooijer and Klein (1989)	One Vector Autoregressive moving average	One-variable Auto Regression Integrated Moving Average (ARIMA)	Antwerp
Zohil and Prijon (1999)	Ordinary least squares regression		Mediterranean
Fung (2001)	Vector Error Correction Model with Structural Identification		Hong Kong
Seabrooke et al. (2003)	Ordinary least squares regression		Hong Kong
Mostafa (2004)	Multilayer Perception Neural Network	ARIMA	Suez Canal
Lam et al. (2004)	Multilayer Perception Neural Network	Linear Multiple Regression	Hong Kong
Hui et al. (2004)	Error Correction Model Approach		Hong Kong
Guo et al. (2005)	The grey Verhulst model	Grey Model (1,1)	
Liu et al. (2007)	Grey Prediction Model and Cubic Polynomial Curve Prediction Model mixed by the Radial Basis Function Neural Network	Radial Basis Function Neural Network With Grey Prediction Model, Radial Basis Function Neural Network With Cubic Polynomial Curve Prediction Model	Shanghai
Mak and Yang (2007)	Approximate Least Squares Support Vector Machine	Support Vector Machine, Least Squares Support Vector Machine, Radial Basis Function Neural Network	Hong Kong
Hwang et al. (2007)	Neuro-Fuzzy Group Method Data Handling Type Neural Networks	Conventional Multilayered Group Method Data Handling Type Neural Networks	Busan
Schulze and Prinz (2009)	Seasonal Auto-Regressive Integrated Moving Average (SARIMA)	Holt–Winters Exponential Smoothing	Germany
Peng and Chu (2009)	The classical decomposition model	Trigonometric regression, regression model with seasonal dummy variables, grey model, hybrid grey model, SARIMA	Taiwan
Gosasang et al. (2011)	Multilayer Perception Neural Network	Linear Regression	Bangkok
Sun (2010)	Conditional Expectation with Probability Distribution		Shandong
Chen and Chen (2010)	Genetic Programming	X-11 Decomposition Approach, Seasonal Auto Regression Integrated Moving Average	Taiwan
Wu and Pan (2010)	Support Vector Machine with Game Theory		Jiujiang
Li and Xu (2011)	Prediction Based on Optimal Combined Forecasting Model	Cubic exponential smoothing, GM (1,1), Multiple regression analysis	Shanghai
Goulielmos and Kaselimi (2011)	The Non-Linear Radial Basis Functions		Piraeus
Zhang and Cui (2011)	Elman neural network, Grey mode		Shanghai
Polat et al. (2011)	Monte Carlo Simulation with Holt–Winters Exponential Smoothing		Turkey
Xiao et al. (2012)	Feed forward neural network with particle swarm optimization		Tianjin
Wang et al. (2013)	Bounded polyhedral set		Asia-Europe
Xie et al. (2013)	Hybrid approaches (SARIMA, seasonal decomposition, classical decomposition) based on least squares support vector regression (LSSVR)	Back-Propagation Neural Networks, support vector regression, ARIMA, SARIMA	Shanghai, Shenzhen
Huang et al. (2014)	Domain knowledge based algorithm	ARIMA with Explanatory Variable	Guangzhou
Xiao et al. (2014)	Transfer forecasting model with discrete particle swarm optimization	Analog complexing, ARIMA, Elman neural network	Shanghai, Ningbo
Tao and Wang (2015)	Multiplicative SARIMA	SARIMA	Shanghai
Anqiang et al. (2015)	Hybrid approaches (SARIMA, LSSVR, ANN)	SARIMA, LSSVR, ANN	Qingdao
Huang et al. (2015a)	Hybrid approaches (SARIMA, genetic programming (GP), projection pursuit regression (PPR))	SARIMA, PPR, ANN	Qingdao

Authors (Years)	Proposed Methodology	Benchmark methodology	Port/Region
Huang et al. (2015b)	Interval knowledge based forecasting paradigm	ARIMA	Qingdao
Zha et al. (2016)	Hybrid approaches (SARIMA, ANN)	SARIMA, ANN	Shanghai
Gao et al. (2016)	Model averaging and Model selection variants	SARIMA	Hong Kong, Shenzhen

All these works produced good results under low uncertainty conditions. However, the 2008/2009 economic crisis showed that deterministic forecasts may be prone to failure in the long term (Pallis and de Langen 2010). More advanced stochastic forecasting methods, which could be able to reflect uncertainty more effectively, are not applied in maritime business because of their complexity and high statistical data requirement (Khashei et al. 2009). On the other hand, simulation could be employed as major component of a forecasting framework combined with deterministic forecasting methods that only need a limited amount of data. Indeed, a simulation-based forecasting framework might be better suited in a stochastic environment where unexpected drops or peaks occur.

In the literature, considerable attention has been given to the service network design of shipping lines under stable demand conditions and on forecasting annual container throughput of ports. However, the impact of seasonal demand fluctuations on service network design is not investigated according to the best knowledge of the authors. Therefore, the main contribution of this paper is to put special emphasis on the impact of seasonal demand fluctuations on the structure of the related H&S networks, the capacity of the fleet operating within the network, the deployment of ship types as well as on the associated routes of the ships. As a case study feeder services for containerized freight in the East Mediterranean and Black Sea region are investigated.

3. THE METHODOLOGY

The dynamic and complex nature of container trade makes accurate forecasting a critical challenge for shipping lines. Therefore, it is important to develop an efficient methodology for forecasting container throughput at the individual ports in order to better assist liner shipping companies in defining their strategies and investment plans.

Essentially, forecasting is a procedure of predicting the future as accurately as possible. In business, the task is typically to predict the development of values for which historical data are available, e.g. demand figures for certain products or services. In such cases, statistical methods can be applied in order to generate the forecasts in a systematic way. Since the future events upon which the actual outcomes are based have not yet been observed, forecasts are always afflicted with an error. Nevertheless, forecasts are inevitable to understand the factors that contribute to future events, to set goals for future achievements and to develop business plans in the short, medium and long term.

In container shipping regional ports face high seasonality in trade volume and, in addition, high demand fluctuations in the short-run (Polat and Uslu 2010; Schulze and Prinz 2009). Therefore, reliable and accurate forecasting is needed to support decision makers in designing their service network, especially, since container shipping involves considerable capital investments and huge daily operating costs. In literature, the proposed models for service network design are typically based on the assumption of stable container demand at ports, which is not realistic in most real applications. Therefore, in this study, a simulation and artificial neural network based forecasting framework is proposed in order to analyze the impact of seasonal demand fluctuation on the design of feeder service networks for containerised freight transportation.

The proposed forecasting framework consists of three modules (see Figure 3). In the first module time series decomposition is applied to convert yearly maritime demand statistics into monthly container throughput figures. The second module consists of an artificial neural network (ANN) based forecasting procedure which is used to analyze trend and seasonality in monthly container throughput. Finally, a simulation module is used to reflect the impact of daily demand fluctuations in container shipping.

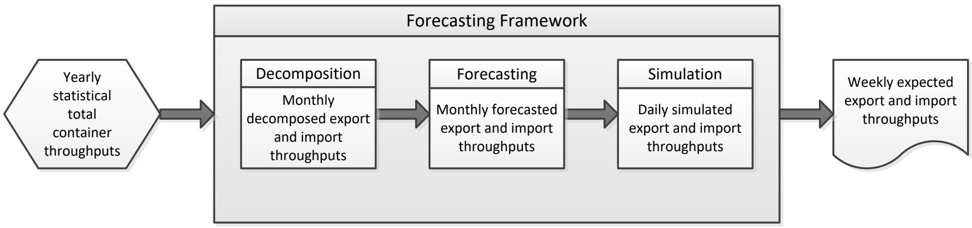

Figure 3. Forecasting framework

Unfortunately, reliable statistics on seasonal container throughput at ports are not freely available (Schulze and Prinz 2009) because shipping lines and container ports usually just provide yearly market shares and total handling amounts. Therefore, the decomposition module in the first step of the forecasting framework decomposes yearly throughput figures into monthly supply and demand quantities. (A detailed explanation of this procedure using empirical data is given in Section 4.2).

The main component of the forecasting framework consists of the ANN based forecasting procedure. ANNs are computational models inspired by the brain and how it processes information. Instead of requiring detailed information about the nature of a system, ANNs try to learn the relationship between the variables and parameters by analyzing data. ANNs can also handle very complex and large systems with many interrelated parameters. The effectiveness of biological neural systems originates from the parallel-distributed processing nature of the biological neurons. An ANN simulates this system by distributing computations to small and simple processing nodes (artificial neurons) in a network. ANNs have been used in many fields. One major application area is forecasting. Due to the characteristic features, ANNs are an attractive and appreciated alternative tool for both research and industrial applications. For comprehensive reviews on the application of ANNs on forecasting, see Zhang et al. (1998) and Kline and Zhang (2004). In conclusion, ANNs are considered an appropriate tool in forecasting container throughput of terminals. In the proposed framework, multi-layer feed-forward networks are trained using back-propagation in order estimate each port's monthly demand and supply throughput.

Figure 4 shows a typical multi-layer feed-forward ANN architecture which contains three layers: an input layer, an output layer and, between them, the hidden layers. Each artificial neuron (node) is linked to nodes of the previous layer with weights. A set of these weights creates the knowledge from the system. In order to produce the desired output for a presented input, the network is trained with a learning method through adaptation of the weights. After the training operation, the weights contain meaningful information about the data. The network uses the corresponding input data to produce output data, which are then compared with the desired output. When there is a difference between desired and produced outputs, the weights continue to adapt in order to decrease the difference (error). Until the total error reaches the required limit, the network continues to run in all the input patterns. After reaching the acceptable level, the ANN stops and uses the trained network to make forecasts. For details of the algorithm, see Zurada (1992) and Bose and Liang (1996).

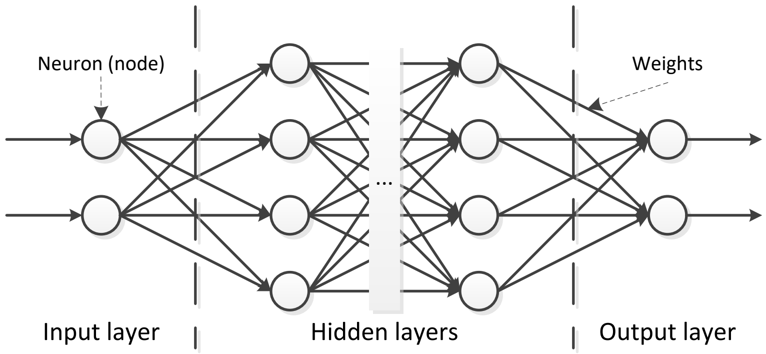

Figure 4. Typical ANN architecture

Back-propagation (BP) is a gradient-descent based effective learning algorithm for ANNs (Rumelhart et al. 1986). By adapting the weights with the gradient, BP tries to reduce the total error. The error is calculated as root-mean-squared (E) value in Equation (1), where t is the produced and o is the desired output over all patterns p and nodes i.

$$E = \frac{1}{2}\left[\sum_{p}\sum_{i}\left|t_{ip} - o_{ip}\right|^{2}\right]^{1/2} \tag{1}$$

The BP algorithm first assigns random values to all weights for all nodes. Then, the activation α_{pi} value is calculated for each pattern and for each node by using the activation function given in Equation (2), where j refers to all nodes of the previous layer, *i* refers to all node positions of the current layer, and x_j and w_{ij} are input and weight terms.

$$\alpha_{pi} = f\left(\sum_{j} x_j w_{ij}\right) \tag{2}$$

After calculating the output of the layer, the error term δ_{pi} for each node is also calculated back through the network. The error term measures the changes in the network by using changes in the weight values. It is calculated for the output nodes and for the sigmoid activation function as given in Equation (3). For hidden layer nodes, the error term is calculated as given in Equation (4), where *k* indicates nodes in the downstream layer and *j* is the position of the weight in each node.

$$\delta_{pi} = \left(t_{pi} - \alpha_{pi}\right)\alpha_{pi}\left(1-\alpha_{pi}\right) \tag{3}$$

$$\delta_{pi} = \alpha_{pi}\left(1-\alpha_{pi}\right)\sum_{k}\delta_{pi}w_{kj} \tag{4}$$

In conclusion, incremental change to each weight for each node is calculated as given in Equation (5), where ε is the learning rate used for weight adaptation in each training iteration and m is the momentum used to change the weight in the previous training iteration w'. Stopping conditions, maximum iteration number, learning rate and momentum are speed and stability constants defined at the beginning of the training.

$$\Delta w_{ij} = \varepsilon\left(\delta_{pi}\alpha_{pi}\right) + m\left(w'_{ij}\right) \tag{5}$$

Finally, the Monte Carlo simulation module uses the monthly throughput figures estimated by the ANNs module as input in order to generate daily demand and supply expectations of container terminals. By analyzing these expectations, shipping lines can obtain realistic data for deciding on vessel capacities, network design, routes, ship deployment and schedules. The simulation model is run a number of times using throughput forecasts from the ANNs. That way, different random samples of future demand and throughput figures of ports are obtained. (See Section 4.2 for an illustration of the simulation mechanism.)

Exact methods for solving the service network design problem are not practical for large-scale problem instances because of the problem complexity (Polat et al. 2012a; Polat et al. 2014). In this study, we therefore use an efficient heuristic solution approach called perturbation based neighbourhood search (PVNS) to determine a near-optimal design of the feeder service network. The PVNS approach applies the Savings Algorithm in order to gain a fast and effective initial solution. An enhanced variable neighbourhood search is used to improve the initial solution by searching neighbourhoods. An adaptive perturbation mechanism is applied to escape from local optima. For details of the algorithm see (Polat et al. 2014; Polat et al. 2015; Polat et al. 2012b). Main output of the heuristic solution algorithm is the composition of the fleet of vehicles and the service routes and their frequency.

4. NUMERICAL INVESTIGATION

4.1. Case study

The countries located in the East Mediterranean and Black Sea region including the Aegean Sea, Marmara Sea and the Sea of Azov (see Figure 5) have faced a substantial increase in total container traffic in recent years. This is mainly caused by the positive economic development of the countries in the entire region. In parallel to the general growth of maritime container traffic an increase in port throughput has also been observed in the regional feeder ports. Hence, the outlook for the maritime transportation market is very promising (Kulak et al. 2013; Varbanova 2011). Several ports in the Mediterranean Sea are directly connected to the trunk shipping lines between Far East and Europe. With these ports as hubs several regional short-sea shipping lines have built up feeder service networks which link the hinterland of this region to the global trunk shipping lines.

Figure 5. Regional ports in the East Mediterranean and Black Sea region

In our numerical experimentation, we consider the case of a particular container feeder line which intends to re-design its feeder service network with a new hub port at Candarli near Izmir, Turkey. Since liner shipping is directly affected by financial, political and seasonal conditions, the company regards seasonal demand fluctuations as a major factor to be included in the design of the service network. In the considered region, the concerned feeder line has 36 contracted container terminals at 26 feeder ports in 12 countries. Table A.1 in the Appendix shows details about the terminals, including country and sub-region information, market share of the shipping lines in the various terminals, and yearly total container throughput between 2005 and 2011. These data are used in our numerical investigation as input to generate weekly throughput figures by use of the forecasting framework proposed in the previous section. Based on these weekly throughput figures the feeder network design is determined from the perspective of the considered feeder shipping line assuming a four-week service time deadline and seven-day service frequency conditions for a 52-week sailing season.

4.2. Demand estimation

For the East Mediterranean and Black Sea region, databases providing information on container throughput of the ports are scarce and it is merely impossible to obtain seasonal throughput figures from the port authorities. For that reason, yearly throughput of regional container terminals is decomposed into monthly supply and demand quantities by using monthly import and export foreign trade rates of the related port countries. Table 3 shows the results of this decomposition procedure taking the Odessa container terminal in 2011 as an example. First, the percentages of monthly export and import trade rates of the yearly foreign trade volumes are calculated. Next, these percentages are applied to determine the monthly container export and import figures for the considered port.

Table 3. An example of monthly throughput decomposition

	1	2	3	4	5	6	7	8	9	10	11	12	Total
Trade Export ($ Million)*	4621	5379	5382	5603	5969	5889	5365	5769	5974	5716	6283	6459	68409
Trade Import ($ Million)*	5037	6463	7016	6298	6766	6772	6522	7208	7412	7545	7675	7892	82606
%-Export in foreign trade	3.06	3.56	3.56	3.71	3.95	3.90	3.55	3.82	3.96	3.79	4.16	4.28	45.3
%-Import in foreign trade	3.34	4.28	4.65	4.17	4.48	4.48	4.32	4.77	4.91	5.00	5.08	5.23	54.7
Container export (TEU)	13883	16160	16169	16833	17933	17693	16118	17332	17948	17173	18876	19405	205523
Container import (TEU)	15133	19417	21078	18921	20327	20345	19594	21656	22269	22669	23058	23710	248177

**Basis: Ukraine's monthly foreign trade in goods (2011), Total throughput of the Odessa container terminal is 453700 TEU in 2011.*

In the subsequent step, the decomposed monthly figures are used in the proposed ANNs approach in order to forecast monthly freight demand and container throughput of the terminals. Figure 6 shows the monthly decomposed demand and throughput figures of the Odessa container terminal between 2005 and 2011 as well as monthly forecasted throughput for 2012.

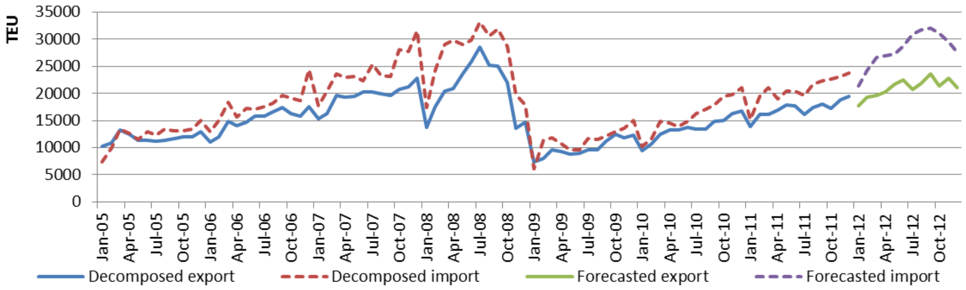

Figure 6. An example of monthly throughputs estimation

In order to reflect fluctuations in daily freight demand, a Monte Carlo simulation model is applied. In the simulation model, the final daily demand figures are randomly generated in a two-step procedure using pre-defined distribution coefficients. The values of these coefficients were defined based on interviews with experts from port authorities and terminal operators. Table 4 shows the coefficients for the variation of demand for days in a week. Three levels of transportation demand are considered: low, medium and high. Taking medium demand as a reference level, low and high demand deviate by +/- 20% from the medium value. The entries in Table 4 indicate respective distribution coefficients for the workload levels and the days of a week. For instance, for Monday a low workload level will be chosen in the random generation of demand values with 20% probability, a low and a high demand level with 40% probability each.

In the second step, randomized day-to-day fluctuations in the course of a month are generated. Table 5 show the respective distribution coefficients used in the simulation procedure. Low and high demand levels deviate by +/- 30% from the medium demand level. It is assumed that transportation demand is distributed over the days of a month according to the distribution coefficients indicated in Table 5.

Table 4. Distribution coefficients for demand of days in a week

Days	Low (0.8)	Medium (1)	High (1.2)
Monday	20%	40%	40%
Tuesday	30%	60%	10%
Wednesday	40%	40%	20%
Thursday	40%	50%	10%
Friday	10%	30%	60%
Saturday	10%	50%	40%
Sunday	50%	40%	10%

Table 5. Distribution coefficients for demand of days of the month

Days	Low (0.7)	Medium (1)	High (1.3)
First 5 days	10%	50%	40%
Mid of the month days	40%	40%	20%
Last 5 days	10%	20%	70%

Table 6 shows a sample calculation of the daily randomized demand generation. For instance, for Oct 05, 2011 (Wednesday) the random number of 0.00543 is drawn from the standard uniform distribution which, according to Table 4, leads to a week-day demand coefficient of 0.80. Next, the second random number of 0.85504 is drawn which according to the cumulative distribution function derived from Table 5 (for the first 5 days of the month) gives a month-day demand coefficient of 1.30. Multiplying these two obtained demand coefficients yields 1.04 and, taking 6405 as the reference demand value for the particular month, results in a randomly generated demand value of 6661. In this way, based on the Monte Carlo simulation principle random demand fluctuations to be used as input for the design of the feeder network are simulated.

Table 6. An example of randomized daily demand generation

Date	Day	Random number	Week-day coefficient	Random number	Month-day coefficient	Combined coefficient	Reference demand	Generated demand
05 Oct. 2011	Wed.	0.00543	0.80	0.85504	1.30	1.04	6405	6661
06 Oct. 2011	Thu.	0.66611	1.00	0.93674	1.30	1.30	6405	8327

In the numerical experimentation, simulation runs are repeated 100 times for each day of each month using forecasted throughput figures. Figure 7 shows the average generated daily demand for export and import of containers for the Odessa container terminal for a 364-day sailing season in 2012. The respective values are assumed as demand forecasts for 2012 derived from historical demand figures. Since the feeder network design problem is solved under the assumption of a seven-day service frequency, daily throughputs are finally aggregated into weekly figures.

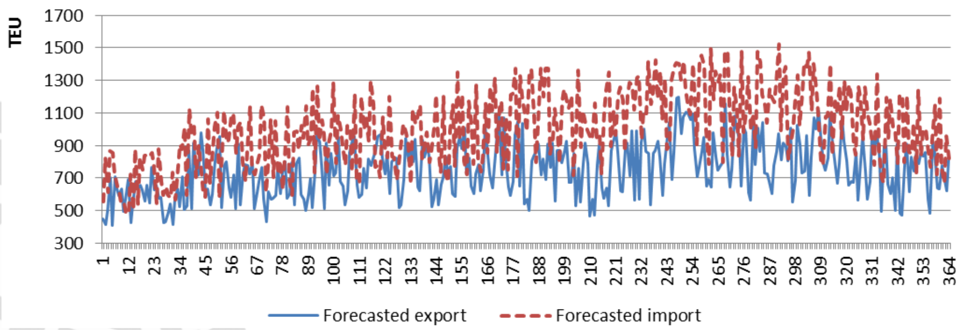

Figure 7. An example of daily transportation demand simulation

Figure 8 shows weekly forecasted demand for export and import of containers for the Odessa container terminal and respective total figures of the region for a 52-week sailing season in 2012. In the next section, these weekly demand forecasts are used in the case study investigation of the feeder service design problem considering seasonally fluctuating transportation demand.

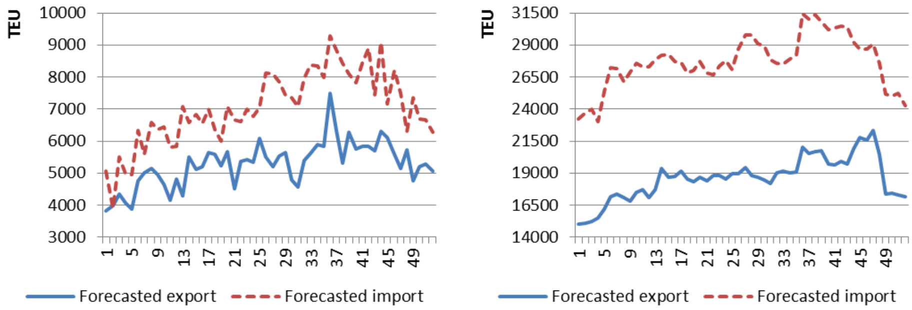

Figure 8. Examples of weekly demand forecasts for the Odessa container terminal (right) and the whole region (left)

4.3. The impact of seasonal demand fluctuations on service network design

Since transportation demand greatly varies during the sailing season, it has a major impact on the service network design for container feeder lines. In particular, the number of ships of different type and the number of service routes will be affected by seasonal demand fluctuations. In this section, we investigate these relationships through a number of numerical experiments using the forecasting framework outlined in Section 3 in order to predict future transportation demand. As an example of application we consider the East Mediterranean and Black Sea region and the network design problem faced by a Turkish feeder shipping line (see Section 4.1). Though shipping lines in practice adapt their feeder service design not until a couple of months, it is assumed in our study that the feeder services are revised at the beginning of every period (week) in response to changes in seasonal demand forecasts. This allows us to better evaluate the impact of demand fluctuations. The revised service network may include introducing new routes and adjusted schedules as well as chartering in new ships or chartering out unnecessary ships.

In order to analyze how seasonal demand fluctuations affect the service network of feeder shipping lines, the developed PVNS approach is run ten times with different random seeds for each week during a 52-week sailing season based on forecasted transportation demand. Figure 9 shows weekly minimum costs for the whole region, including chartering costs, operating costs, administration costs, on-sea bunker costs, on-port bunker cost and port charges for a 52-week sailing season. In other words, the figure shows how seasonal fluctuations of transportation demand affect the total feeder service costs of the region. Total costs vary between \$4.6 million and \$6.17 million indicating a 34.13% cost difference between the 1st and 38th week of the sailing season.

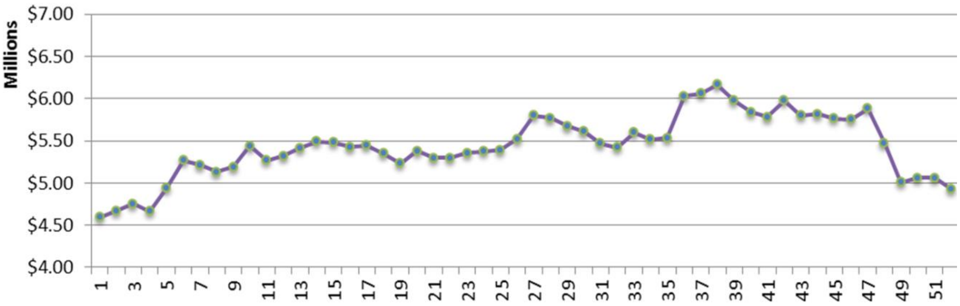

Figure 9. Minimum total cost of the region for a 52-week sailing season

Since the geographic dimensions of feeder networks are far smaller than those of trunk line networks, total network costs contain a higher degree of ship-based fixed costs, such as chartering, operating and administration. Therefore, the cost difference from week to week mainly results from the number of service routes, the number of necessary ships and the types of these ships.

As can be seen from Figure 10 the optimal number of routes in the network varies between 13 and 17. Since the hub port in Candarli is located close to the feeder ports, a large portion of small and mid-sized containerships is employed in the low demand seasons, while mid-sized containerships dominate in regular demand seasons, and big ships are only employed in order to cover peak demand. As a result, 34.70% of the routes are serviced by small ships, 64.78% by mid-sized ships, and 0.53% by big ships. Of the total slot capacity of the fleet 19.61% attribute to small ships, 79.32% to mid-sized ships, and 1.07% to big ships. The necessary slot capacity varies between 25,400 TEU (28.35% for small and 71.65% for mid-sized ships) and 37,500 TEU (19.20% for small, 69.33% for mid-sized and 11.47% for big ships), which corresponds to a 47.64% difference between the low demand (week 1) and the high demand season (week 37) of the sailing season.

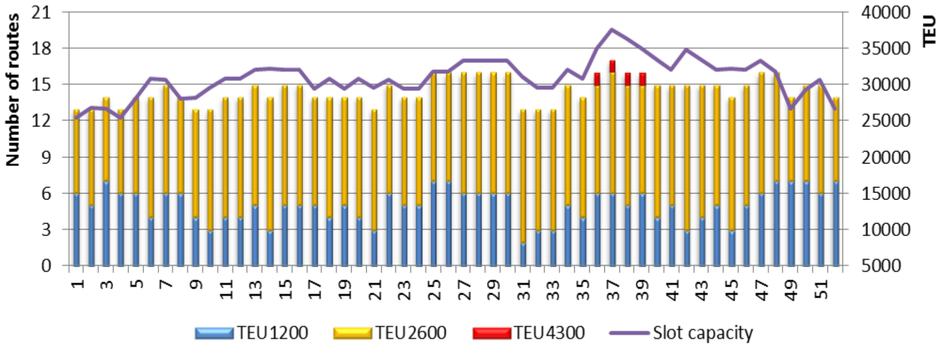

Figure 10. Necessary number of routes with ship types and slot capacity

Figure 11 shows how the composition of the fleet varies during the sailing season. It appears that the fleet size of the service network varies between 23 ships (39.13% small and 60.87% mid-sized) and 30 ships (30.00% small, 63.33% mid-sized and 6.67% big ships). These figures represent the minimum number of ships required for a seven-day frequency based on weekly forecasts of transportation demand for a 52-week sailing season.

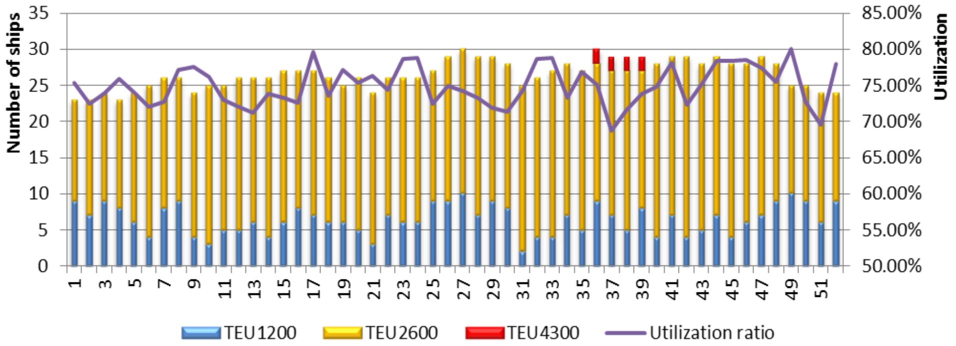

Figure 11. Necessary minimum number of ships of various types and capacity utilization

5. CONCLUSIONS

Decisions on feeder network design, e.g. on fleet size and mix, fleet deployment, ship routing and scheduling, are usually based on estimates of the container transportation volume in the considered region. However, transportation volume is highly affected by unstable economic and political conditions as well as seasonal demand fluctuations. In this study, we propose a Monte Carlo simulation and artificial neural network based forecasting framework to analyze the impact of these conditions on service network design of container feeder lines. Therefore, the service network design is updated repeatedly in the course of the year. As a methodology to solve the underlying combinatorial optimization problem, a perturbation based variable neighbourhood search approach is employed.

The proposed model implementation has been tested for the liner shipping feeder service in the East Mediterranean and Black Sea region taking the design problem of a Turkish short-sea shipping company in view of the opening of the new Candarli port near Izmir, Turkey as an example. The optimal service network is determined based on the forecasted container throughput of the terminals in the region for each week during a 52-week sailing season. The results show that total costs of the service network as well as the necessary total slot capacity greatly vary over the sailing season. Moreover, the size and mix of the fleet of ships is highly affected by unstable demand conditions. These figures show the importance of dynamic and flexible service network design for container feeder lines. This study could be extended by developing a modelling approach for robust multi-period service network design and to investigate contractual relationships with customers as well as collaboration schemes between different shipping lines in the region.

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Appendix

Table A.1. Figures of contracted container terminals*

	Terminal	Country	Share**	2005***	2006	2007	2008	2009	2010	2011
1	Burgas	Bulgaria	31.0%	25000	26400	30600	45900	23800	23500	25000
2	Varna	Bulgaria	21.0%	84000	94000	99700	155300	112600	118700	122844
3	Constanta 1	Romania	19.0%	476600	737100	1111400	1080900	294300	256500	350000
4	Constanta 2	Romania	24.0%	300000	300000	300000	300000	300000	300000	300000
5	Illiychevsk	Ukraine	20.0%	291100	312100	532800	670600	256800	301500	280000
6	Odessa	Ukraine	22.0%	288400	395600	523500	572100	255500	354500	453700
7	Novorossiysk 1	Russia	29.0%	-	60000	90100	182000	84000	188652	335847
8	Novorossiysk 2	Russia	29.0%	-	99100	141400	124500	111000	124626	200153
9	Poti	Georgia	20.0%	105900	126900	184800	209600	172800	209800	254022
10	Batumi	Georgia	20.0%	-	-	-	44200	8800	16300	45439
11	Trabzon	Turkey	35.0%	300	5400	22300	22100	21100	34072	40251
12	Haydarpasa	Turkey	15.0%	340600	400100	369600	356300	191400	176500	206082
13	Ambarli 1	Turkey	10.0%	790300	962900	1296800	1541200	1263600	1663600	1548485
14	Ambarli 2	Turkey	15.0%	439000	531000	666000	649000	476000	621000	844000
15	Ambarli 3	Turkey	15.0%	161500	198500	276300	359700	200200	376400	449400
16	Gebze 1	Turkey	15.0%	33800	35800	68800	135500	133400	184500	230884
17	Gebze 2	Turkey	15.0%	14000	33000	78000	118000	156300	248200	283903
18	Gemlik 1	Turkey	15.0%	90500	94800	114500	141000	152300	200500	195021
19	Gemlik 2	Turkey	15.0%	240500	274600	341300	336300	214100	269300	462987
20	Gemlik 3	Turkey	15.0%	-	-	-	21800	84700	108100	107322
21	Aliaga 1	Turkey	15.0%	-	-	-	-	-	139918	256598
22	Aliaga 2	Turkey	15.0%	-	-	-	-	-	99414	127961
23	İzmir	Turkey	14.0%	784400	847900	898200	884900	826600	726700	672486
24	Thessaloniki	Greece	13.0%	366000	344000	447000	239000	270200	273300	295870
25	Piraeus 1	Greece	13.0%	1394500	1403400	1373100	433600	498838	178919	490904
26	Piraeus 2	Greece	12.0%	-	-	-	-	166062	684881	1188100
27	Antalya	Turkey	15.0%	11800	40200	63400	67100	59500	125700	165474
28	Mersin	Turkey	9.0%	594243	632905	799532	869596	845117	1015567	1126866
29	Limassol	Cyprus	10.0%	320100	358100	377000	417000	353700	348400	345614
30	Lattakia	Syria	9.0%	390800	472000	546600	568200	621377	586283	524614
31	Beirut	Lebanon	8.0%	463700	594200	947200	945134	994601	949155	1034249
32	Haifa	Israel	9.0%	1123000	1070000	1170000	1396000	1140000	1263552	1235000
33	Ashdod	Israel	11.0%	587000	693000	809000	828000	893000	1015000	1176000
34	Alexandria 1	Egypt	7.0%	733900	762000	977000	632250	638700	666500	757572
35	Alexandria 2	Egypt	5.0%	-	-	-	632250	638700	666500	700000
36	Damietta	Egypt	8.0%	1129600	830100	894200	1125000	1139000	1060100	800000

Source: Dynamar (2009), Ocean Shipping Consultants (2011) and web pages of container terminals. ** Market share of the considered feeder shipping line at the container terminal * Total throughput of container terminal in TEU*