WHICH FORECASTING MODELS ARE EMPLOYED IN THE SHIPPING INDUSTRY? IDENTIFYING KEY THEMES AND FUTURE DIRECTIONS THROUGH AN INTEGRATIVE REVIEW

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SUMMARY

Developing accurate forecasting models provides the capability of handling the uncertain, volatile, and complex nature of the shipping industry. The outcome of the forecasts directly affects the decisions of policymakers. In this case, numerous forecasting studies have been published over time and rapid development has been evolved to reach accurate forecasts. This paper reviews both analytical and empirical studies by categorizing forecasting themes for shipping. The focus is threefold: to examine the developed forecasting models, to analyse the employed specific features and to evaluate the data characteristics, used variables, forecasting methods and models, and model features. Furthermore, a future agenda and implications to the industry are proposed. The findings are considered to provide information that is useful for researchers and practitioners who are involved in the forecasting process of the shipping industry.

NOMENCLATURE

ABC	*Artificial Bee Colony*
AC	*Analog Complexing Algorithm*
AGA	*Adaptive Genetic Algorithm*
ANN	*Artificial Neural Network*
APSO	*Improved Particle Swarm Optimization*
AR	*Autoregression Model*
ARCH	*Autoregressive Conditional Heteroscedasticity*
ARIMA	*Autoregressive Integrated Moving Average*
ARIMARCH	*The Combination of ARIMA And ARCH Model*
ARIMAX	*An Autoregressive Integrated Moving Average with Exogenous Variables*
ARMA	*Autoregressive Moving Average*
BDI	*Baltic Dry Index*
BELM	*Butterfly Optimization Algorithm*
Bi-cFTS	*Bivariate cFTS*
BP	*Backpropagation Neural Network*
CCFI	*China Containerized Freight Index*
CCGA	*Chaotic Cloud Genetic Algorithm*
CDM	*Classical Decomposition*
CEEMD	*Complementary Ensemble Empirical Mode Decomposition*
cFTS	*Univariate C-Means Fuzzy Time Series*
CGE	*Computable General Equilibrium*
CSAPSO	*Chaotic Simulated Annealing Particle Swarm Optimization*
DBECI	*The Dry Bulk Economic Climate Index*
DEA	*Data Envelopment Analysis*
DFA	*Dynamic Factor Analysis*
ECM	*Error Correction Model*
EEMD	*Ensemble Empirical Mode Decomposition*
EGARCH	*Extended GARCH*
ELM	*Extreme Learning Machine*
EMD	*Empirical Mode Decomposition*
FANN	*Fuzzy ANN*
FGM	*Fourier Modified Grey Model*
FILF	*Fuzzy Integrated Logical Forecasting Method*
FNN	*Feed Forward Neural Network*
FSARIMA	*Fourier Modified SARIMA*
FTS	*Fuzzy Time Series*
GA	*Genetic Algorithm*
GARCH	*The Generalized Autoregressive Conditional Heteroskedasticity*
GDP	*Gross Domestic Product*
G-vSVR	*V-Support Vector Regression Hybridized with Gauss Function*
GM	*Grey Model*
GP	*Genetic Programming*
GRNN	*General Regression Neural Network*
GSA	*Gravitational Search Algorithm*
GWO	*Grey Wolf Optimization*
HEGY	*Hylleberg-Engle-Granger-Yoo statistics*
HFMG	*Hybrid Forecasting Model Based On GMDH*
HGWO	*Hybridizing Grey Wolf Optimization*
HW	*Holt-Winters (Exponential Smoothing) Model*
IBPNN	*Input Vector Decision Method Backpropagation*
IGvSVR	*Hybridization of IVD with G-vSVR*
IPI	*Industrial Production Index*
KELM	*Kernel Extreme Learning Machine*
KGRNN	*Generalized Regression Neural Network and KPCA Algorithm*
KPCA	*Kernel Principle Component Algorithm*
KRSVR-C^{cat}CSAGA	*Hybridizing RSVR with Chaos Operation by Cat Mapping and KPCA Algorithm*
KRSVR-C^{logistic}SAGA	*Hybridizing RSVR with Chaos Operation by Logistic mapping and KPCA Algorithm*
LM	*Levenberg-Marquardt*
LSSVM	*Least Square Support Vector Machine*

MLP	*Multilayer Perceptron Model*
MNR	*Multiple Nonlinear Regression*
PCA	*Principal Component Analysis*
PPR	*Projection Pursuit Regression*
PRSVR-C^{cat}CSAGA	*Hybridizing RSVR with Chaos Operation by Cat Mapping and PCA*
PSO	*Particle Swarm Optimization*
PX	*Price*
RBF	*Radial Basis Function Neural Network*
RSVR	*The Robust V-Support Vector Regression Model*
SA	*Simulated Annealing Algorithm*
SAPSO	*Simulated Annealing Particle Swarm Optimization*
SARIMA	*Seasonal Autoregressive Integrated Moving Average*
SARIMANT	*Seasonal ARIMA without transformation and interventions*
SD	*Secondary Decomposition*
SECM	*Structural Error-Correction Model*
SEM	*Structural Equation Model*
S-VECM	*Restricted VECM*
SVM	*Support Vector Machine*
SVR	*Support Vector Regression*
TF-DPSO	*Transfer Forecasting Model Guided by Discrete Particle Swarm Optimization Algorithm*
TRM	*Trigonometric Regression Model*
VAR	*Vector Autoregression*
VARMA	*Vector Auto Regressive Moving Average*
VARX	*Vector Autoregressive Model with Exogenous Variables*
VECM	*Vector Error Correction Model*
VMD	*Variational Mode Decomposition*
WD	*Wavelet Decomposition*
WPD	*Wavelet Packet Decomposition*

1. INTRODUCTION

Forecasting the future is crucial for the shipping industry stakeholders to make investment decisions on ordering a ship, establishing the chartering type, planning the future, gaining more profit and calculating the risk (Stopford, 2009). Moreover, further digital transformation, potential transport infrastructure needs, and increased investment in ships (UNCTAD, 2018), promoting low carbon shipping and transport connectivity, autonomous shipping (UNCTAD, 2020) will boost the importance of forecasting for the shipping industry in the future. One example is the port infrastructure investment, it is forecasted to be $68 billion in 2027 (The Global Infrastructure Hub, 2020). Similarly, the cumulative investment needed for the achievement of IMO's 2050 decarbonization goals is estimated to be approximately USD 1-1.4 trillion (Krantz et al. 2020). Hence, the establishment of a decision support system based on accurate forecasts is needed to ensure optimal investment decisions.

As the industry need for accurate forecasts has increased, the related literature developing forecasting models has also grown. Forecasting and modelling shipping markets have been studied for years, though it has attracted much attention widely in the last decades (Nielsen et al. 2014). The earliest studies found during the review as Tinbergen, (1959); Beenstock and Vergottis, (1993); Charemza and Gronicki, (1981) are generally shown a theoretical foundation. Several articles on shipping forecasting have been published after 2000, and many of them indicate empirical research and focus on quantitative models using different forecasting techniques as econometric modeling (e.g., Yong Hui et al. 2014; Zhang et al. 2014; Rashed et al. 2018; Gavriilisdis et al. 2018), time series (e.g., Rashed et al. 2017; Munim and Schram, 2017; Tsioumas et al. 2017), soft computing techniques (e.g., Geng et al. 2015; Bao et al. 2016, Chen et al. 2020).

While there have been prior literature reviews of demand forecasting in freight transport (e.g., Chow et al. 2010; Tavasszy et al. 2012); few efforts (e.g., Parola et al. 2020) have been made to investigate shipping forecasting cases, methods, and implications. Parola et al. (2020) investigated port traffic forecasting studies from the perspective of port authorities. They also implied the need for more in-depth analysis. This paper is designed to fill this gap through an integrative review, and it explores the used methods and identifies the forecasting cases from a wider perspective. The main objective is, therefore, to investigate the existing empirical literature on shipping forecasts and to propose future research directions based on the new trends and recent advances.

This paper is an integrative literature survey paper that focuses extensively on forecasting studies in shipping. Through this review, a total of 161 publications are identified over the period 1973-2020 and lists of these studies are provided in the following section. To the best of our knowledge, this research is the first review paper that considers the prior forecasting studies in shipping. The highlighted goals pursued in this paper:
(1) Publications are analysed systematically highlighting the development of the literature by considering data characteristics, methodology, and themes.
(2) A future agenda and discussions on implications to the shipping industry are proposed.

In order to achieve the objectives of this paper integrative literature review method by Cooper (1982) has been adopted. We conducted these steps: Problem formulation, data collection, evaluation of the data, analysis and interpretation, and presentation. First, the following research questions have been generated:

Which forecasting models are employed and dominant in the shipping industry?
What are the characteristics of the data used while developing forecasts for the shipping industry?
What are the forecasting research gaps that are not issued in the shipping literature?
During the data collection stage, we have conducted iterative searches within various databases such as WoS,

Google Scholar, Scopus. To find out relevant studies, the following terms are used: “Shipping forecast”, “shipping + forecast”, “freight rate forecast”, “merchant fleet forecast, “average haul forecast”, “ship productivity forecast”, “ship demand forecast”, “seaport forecast”, “maritime forecast”. Keywords are selected based on the forecasting categories specified by Stopford (2009).

The last search was conducted in December 2020. The literature search has been identified 3543 articles of potential interest. During this search, publications only written in English were regarded and 3356 publications were retrieved. After eliminating duplications, 2551 were collected for review. After the title, abstract and full-text screenings, the data evaluation stage has been conducted considering the research questions of this paper. Besides this database search, backward snowballing has also been used to reach publications as much as possible. We have ended up at this stage with a total of 161 publications. Analysis and interpretation, and presentation of the conducted review have been presented in the following sections.

The rest of the paper is designed as the following sections: In section 2, characteristics of data considering seasonality, volatility, cyclicality, data aggregation, and disaggregation and explanatory variables, are briefly described. Then, methodological developments and key approaches in classification are given. In Section 3, forecasting studies in shipping are summarized according to their themes. In Section 4, a future research agenda is proposed. In the last section, conclusions are discussed.

2. EMPIRICAL FINDINGS OF THE RESEARCH

The main features of the shipping market are seasonality, cyclicality, high volatility, and capital intensity (Zhang et al. 2014). The publications frequently focus on these features. In this sense, the current review provides an insight into these characteristics in shipping modelling and forecasting. This section of the paper summarizes the data characteristics, methodological developments, and forecasting studies regarding their themes to reveal the state of the arts.

2.1. CHARACTERISTICS OF DATA AND SOURCES

Model development of forecasting studies in shipping generally relies on secondary data. Primary data and complementary models are neglected in the literature. Forecasting case depends on the characteristics of the data, data availability, researchers’ background and resilience, and previous empirical research. Out of 161 total publications, 68 used monthly data, 38 used annual data, 10 used quarterly data, 21 used daily data, and 11 used weekly data.

The concentration of the publications belongs to freight rate forecasting and port traffic forecasting. First, freight rate forecasting contains 27 distinct source titles with a total of 49 publications. Maritime Economics and Logistics published 13 of the total publications which count for approximately 27% of the fields’ publications. Second, port traffic forecasting has 44 distinct source titles with a total of 58 publications. Maritime Policy and Management have a higher number of publications (6) which counts for approximately 10% of the fields’ publications. In terms of the total forecasting studies regarding the shipping industry, analysed publications have mainly been published in some of the key maritime journals such as Maritime Policy and Management (25) and Maritime Economics and Logistics (24). Besides these journals, computing journals such as Expert Systems with Applications (4), Applied Soft Computing (3), Neurocomputing (3) are published several articles.

2.1.1. Seasonality

When daily, weekly, monthly and quarterly data are used as of this literature review, seasonality should be considered in the modelling process. Yin and Shi (2018) preferred monthly data instead of weekly to avoid complex mathematical problems while using HEGY method. Similarly, Poblacion (2015) used monthly averages from weekly estimated series to confirm the seasonality in freight rates. The reason for preferring monthly data in the studies was also be supported by the statement of Hyndman and Athanasopoulos (2018) that usage of weekly and daily data has challenging due to the complex seasonality patterns.

Denning et al. (1994) test the seasonality and found the presence of the seasonality at the BFI index value. However, they proposed the lack of a seasonal pattern in the futures contract. Kavussanos and Alizadeh (2001) investigated the seasonality patterns in dry bulk shipping. They found deterministic seasonality in individual months while rejecting stochastic seasonality. Kavussanos and Alizadeh (2002a) analysed the seasonality patterns in tanker markets. They found deterministic seasonality in November and December while rejecting stochastic seasonality. Similarly, Yin and Shi (2018) analysed the seasonality patterns in container freight rates. They searched for both deterministic and stochastic seasonality with HEGY method and Monte Carlo method and seasonal dummy variables. They found deterministic seasonality in March and October while rejecting stochastic seasonality. Poblacion (2015) incorporated seasonality while forecasting freight rates. In contrary to Kavussanos and Alizadeh (2002a), Poblacion (2015) found that seasonality is stochastic instead of deterministic.

In terms of port traffic forecasting, it is also found in some studies that (e.g., Chen and Chen, 2010; Farhan and Ong, 2016) as consistent with the Shu et al. (2013) the cargo throughput has the characteristic of seasonality. Recent studies have focused on seasonality and decomposition methods (e.g., Xie et al. 2013, Du et al. 2019). HEGY Test

(Hylleberg et al. 1990) is widely used while detecting seasonality. Only a few of the studies have evaluated seasonality by HEGY or an alternative test. Schulze and Prinz (2009) conducted HEGY test with quarterly data and found seasonal unit root. Xie et al. (2013) relied on the previous literature while considering seasonality. Mo et al. (2018) used HEGY test with monthly data and found seasonality characteristics.

Peng and Chu (2009) analysed the seasonal variations by six univariate models including the CDM, TRM, regression model with seasonal dummy variables, GM, hybrid GM, and the SARIMA model. The seasonality component has been ignored in most of the research due to its complexity. However, there is still a need for further investigation into the nature of the seasonality in shipping cases with different time horizons, regions, and variables.

2.1.2. Volatility

There is a growing literature on forecasting the volatility of shipping markets. Kavussanos (1996) compared volatility in the dry bulk industry and proposed that the volatility is higher in charter markets. In the dry bulk industry, Chen and Wang (2004) presented an asymmetric effect between past innovations and current volatility, while Jing et al. (2008) proposed that asymmetric features are dependent on market segments and conditions. However, Drobetz et al. (2012) could not observe asymmetric effects in the dry bulk freight market. Alizadeh and Nomikos (2011) proposed that the volatility of the freight rates is associated with the form of the term structure. While Leonov and Nikolov (2012) used WD and Zeng and Qu (2014) preferred EMD to investigate the volatility of dry bulk shipping indices.

For the tanker freight market, Adland and Cullinane (2006) found spot freight rate level effects in the conditional volatility of spot freight rate changes. Similarly, Drobetz et al. (2012) presented asymmetric effects in the tanker freight market. Sun et al. (2014) focused on the multiscale relevance between freight rates and oil prices and found different multiscale properties. Li et al. (2018) investigated oil price volatility and its role in the volatility of the tanker freight market. Similarly, Gavriilidis et al. (2018) investigated the effect of oil price shocks as the explanatory variable on the accuracy of the volatility forecasts and they suggest a significant improvement. However, Lauenstein and Walther (2016) found that asymmetry does not enhance the performance of the forecasts. Zhang and Zeng (2017) used EMD and MVGARCH to analyse the volatility of the tanker freight market.

The literature on the volatility of the shipping markets has a wide range of empirical research. Recently, there is also growing literature on volatility spillovers across shipping markets (e.g., Tsouknidis, 2016; Li et al. 2019; Hsiao et al. 2014). As a remark, despite mentioning the importance of the volatility here, we by no means try to be comprehensive on this issue. We hence focus on examining the related papers in shipping forecasts.

2.1.3. Shipping Cycles

Shipping cycles dates to 1741 and 22 cycles are identified since then (Stopford, 2009). Predicting cycles have high practical value as a guideline for developing an appropriate ship investment strategy plan (Jeon et al. 2020). However, there has been limited literature focusing on this issue. Randers and Gölüke (2007) used 1–4 years horizon for the cycle of the shipping freight rate. Goulielmos and Psifias (2011) suggested the shipping cycle of dry bulk shipping for strategic planning lasts 4 years. Christe and Van Vuuren (2014) used BDI data to explore cyclicality using Fourier Analysis. They proposed 4 years and 7 years of shipping cycles. Similarly, Papailias et al. (2017) investigated cyclicality with trigonometric regression in BDI and found a strong cyclical pattern duration of 3 and 5 years.

Recently, Jeon et al. (2020) analyzed cyclicality with system dynamics in CCFI and described time variation as 1-4 years which tends to be shorter than other shipping freight cycles. 5 years of shipping cycle periods are considered while assessing investment decisions by Yin et al. (2019). Chen et al. (2019) investigated the cycle duration of Aframax tanker's freight and resulted in a quarterly cycle of 11.2 months, a short-term cycle of 3.7 years, and a medium-to-long-term cycle of 11.9 years. Siddiqui and Basu (2020) employed the complete ensemble empirical mode decomposition method to extract the cyclical components relating to the oil prices. They offered a research direction focusing on the causality of various cycles that are discovered. Similarly, Fei et al. (2020) detected the lacked assessment of the literature on the non-periodic cycle and explaining the impact of qualitative events in a quantitative way.

2.1.4. Data Disaggregation

Most analysed forecasting studies in shipping are grounded on aggregated data (port handling volume or regional handling volume). However, data aggregation is an issue of the accuracy of the forecasting methods as it could provide more detailed results (Song and Li, 2008). There is little research that specifically mentioned data aggregation and analysed studies have different perspectives on it. If the major forecasting theme is freight rate and prices at the freight markets, disaggregated data could reach more accurate results.

Tsolakis et al. (2003) used disaggregated data to forecast second-hand ships and specified that disaggregated data provides a detailed understanding of each market segment. However, if the forecasting theme is port traffic forecast, aggregated data could result in better performance. Pang and Gebka (2017) found that terminal-level data suffers more from structural breaks rather than the aggregated total throughput.

2.1.5. Explanatory Variables

Recent studies have heavily emphasized the explanatory variables as the inclusion of explanatory variables might improve the forecasting models as found by Gavriilidis et al. (2018), Tsioumas et al. (2017) and Yang and Mehmed (2019). During the review, some specific variables have been encountered such as DBECI, Fleet development, steel output (Tsioumas et al. 2017), aggregate oil demand shock, precautionary oil specific demand shock and oil supply shock (Gavriilidis et al. 2018). Table 1 shows the most used variables while modelling forecasts for the shipping industry. It is observed from the reviewed studies that models tend to include explanatory variables over time. However, there is no commonly agreed variable in certain forecasting cases. GDP, Export, import, newbuilding prices, cargo throughput, trade volume, fleet size/capacity are the most used variables while modelling the shipping forecasts.

2.2. METHODOLOGICAL DEVELOPMENTS

The timeline of the forecasting methods used in shipping with reviewed studies is illustrated in Figure 1. It shows an overview of the progress accomplished by the previous literature. It has appeared that there has indeed been a significant leap forward since the 2000s in terms of the number of studies and methods used. Qualitative forecasting techniques have not attracted much attention, only a few qualitative studies have been found during the review. The models especially developed by quantitative methods have complicated and hybridized after 2010. An interest in the forecasting in shipping has been aroused over years, and it is expected that in the coming years, more articles that hybridized the methods and techniques will be published.

Used methods before 2000 were traditional methods such as the multinomial probit model (Winston, 1981) and simple regression models (Tongzon, 1991; Tambakis, 1984), time series models such as ARMA, ARIMA, VARMA (De Gooijer and Klein, 1989); SARIMA, SARIMANT (Klein, 1996), VAR (Veenstra and Franses, 1997). Markov Chain models were proposed as a useful tool for port management and trade diversion research by Chu (1979). Moreover, qualitative methods were employed by Ariel (1989) and Wing (1973). Li and Parsons (1997) compared the traditional method ARMA with ANN. They proposed that ANN consistently outperformed for longer-term forecasting. After this pioneering study, soft computing methods have become used.

Mostafa (2004), and Lyridis et al. (2004), Lam et al. (2004) and Satir et al. (2008) forecasted using ANN. Moreover, SVM was proposed by Yang et al. (2008) as a new effective practicable approach to predict freight rate in the shipping market. Along with the soft computing models, traditional methods have been used increasingly between 2000 and 2010. After 2010, models have started to be more complex and hybridized. To find out more accurate forecasts researchers have used hybrid approaches such as combining soft computing and soft computing methods (e.g., Li et al. 2015), combining traditional methods and soft computing (e.g., Xie et al. 2013).

At the same time, seasonality (Schulze and Printz, 2009), decomposition (e.g., Peng and Chu, 2009), lags (e.g. Kavussanos and Alizadeh, 2002a) and causality (e.g. Alizadeh et al. 2007) have been considered more frequently. Volatility has become important and several methods have been employed to overcome this issue (e.g., Yong Hui et al. 2014; Zeng and Qu, 2014). Moreover, different decomposition methods have been increasingly adopted (e.g., Leonov and Nikolov, 2012; Zeng and Qu, 2014; Zeng et al. 2016). Although the literature provides plenty of research, there is still no consensus on which models should use in which forecasting case.

Data pre-processing-based hybrid models provide the transformation of time series into simpler data or several sub-datasets. Trend, seasonality, cycle, and irregular fluctuation parts of the time series can be decomposed to get more accurate forecast results. Data pre-processing-based hybrid models are the most popular and widely used hybrid models (Hajirahimi and Khashei, 2019). In shipping, the literature on data pre-processing-based hybrid models is a relatively new, growing, and valued research topic. Xie et al. (2013) applied SARIMA, CD, and SD to decompose and hybridized with LSSVR, NN, and SVR. Ruiz Aguilar (2014) used SARIMA-SVM model as a series hybrid structure to forecast the inspection volume. Leonov and Nikolov (2012) used wavelet decomposition with a neural network algorithm while Zhang et al. (2019) preferred a dynamic fluctuation network with neural network algorithms for forecasting dry bulk indices. Xiao et al. (2016) combined neural networks and the wavelet transform. Zeng and Qu (2014), Mo et al. (2018) and Shankar et al. (2019) provided some pre-processing-based hybrid models.

Parameter optimization-based hybrid models especially with metaheuristic algorithms have been used in shipping as well. Liu et al. (2014) presented APSO optimization with LSSVM. Xiao et al. (2014) applied DPSO optimization. Li et al. (2015) used C^{cat}SAGA, while Geng et al. (2015) used CSAPSO to parameter optimization for port throughput forecasting. Huang et al. (2015) preferred GA to optimize PPR. Gokkus et al. (2017) used ABC to optimize parameters of NN and GA to optimize the parameters of MNR. Li et al. (2017) proposed CCGA due to its optimization superiorities among other evolutionary algorithms as DE, PSO, SA, CSAPSO.

In some research, both pre-processed and ensemble hybrid models have been simultaneously preferred (e.g., Xie et al. 2017, Li et al. 2019). Niu et al. (2018) pre-processed data with VMD, optimized parameters with GWO and ensembled it with SVR for container throughput

Table 1**.** Explanatory Variables used in Shipping Forecast Literature

VARIABLES AT SHIPPING FORECAST LITERATURE / **VARIABLES** / **REFERENCES**	1.Exchange Rate	2.Export	3.Import	4.Population	5.IPI	6.GDP/GNP	7.Distance	8.Oil Price	9.Oil Production	10.New Building PX	11.Second-Hand PX	12.Demolition PX	13.Trade Volume	14.Trade Value	15.Freight Index	16.Cargo Throughput	17.Freight Rate	18.Fleet Size/Capacity	19.Demolition Vol.	20.Interest Rates	21.Inflation Rates	22.Seasonality	23.Charter Rates	24.Elect.Consumption	25.Profits	26.Commodity	27.Order Book	28.Expnd of Building & construction
Seaborne Trade Forecast																												
Bablock and Lu, 2002																						x						
Claessens et al. 1984		x				x	x																					
Chou et al. 2008		x	x	x	x	x																						
Chu, 1979		x	x																									
De Langen, 2003		x				x							x	x														
Hsu et al. 2020		x	x																							x		
Li et al. 2015		x	x			x							x			x												
Li et al. 2020						x							x															
Lun and Quaddus, 2008										x	x	x	x				x	x										
Lyk-Jensen, 2011	x	x		x		x	x																					
Winston, 1981													x				x									x		
Merchant Fleet Forecast																												
Erdoğan and Sengöz, 2007	x					x							x		x			x		x	x					x		
Luo et al. 2009								x		x		x				x	x	x										
Wada et al. 2018						x	x						x						x								x	
Freight Rate Forecast																												
Chang et al. 2012									x	x	x						x											
Chen et al. 2012	x				x										x													
Eslami et al. 2016				x			x	x		x		x						x				x					x	
Geomelos and Xideas, 2014						x				x	x	x	x					x					x					
Jonnala et al. 2002							x															x						
Kavussanos and Alizadeh, 2002b										x	x	x													x			
Lyridis et al. 2004								x	x	x	x	x	x					x					x					
Lyridis et al. 2013										x	x	x					x						x		x		x	
Munim and Schramm, 2017															x													
Munim and Schramm, 2020										x								x					x					
Nielsen et al. 2014															x		x					x						
Papailias et al. 2017	x					x		x																		x		
Santos et al. 2014									x	x		x							x				x					
Siddiui and Basu, 2020								x																				
Yang et al. 2008															x													
Yang and Mehmed 2019															x													
Port Throughput Forecast																												
Coto Millan et al. 2013		x	x			x											x									x		
Dragan et al. 2020	x	x	x			x																						
Fung, 2001														x		x												
Fung, 2002														x		x												
Geng et al. 2015		x	x	x		x																						
Gosasang et al. 2010	x			x		x		x												x	x							
Gokkus et al. 2017		x		x		x							x															

Table 1. Explanatory Variables used in Shipping Forecast Literature (Continued)

VARIABLES AT SHIPPING FORECAST LITERATURE / VARIABLES / REFERENCES	1.Exchange Rate	2.Export	3.Import	4.Population	5.IPI	6.GDP/GNP	7.Distance	8.Oil Price	9.Oil Production	10.New Building PX	11.Second-Hand PX	12.Demolition PX	13.Trade Volume	14.Trade Value	15.Freight Index	16.Cargo Throughput	17.Freight Rate	18.Fleet Size/Capacity	19.Demolition Vol.	20.Interest Rates	21.Inflation Rates	22.Seasonality	23.Charter Rates	24.Elect.Consumption	25.Profits	26.Commodity	27.Order Book	28.Expnd of building & construction
Port Throughput Forecast																												
Hui et al. 2004														x		x												
Jugović et al. 2011		x	x																									
Lam et al. 2004		x	x	x		x								x										x				x
Patil and Sahu., 2016	x	x	x			x			x																			
Patil and Sahu., 2017						x										x												
Sahu and Patil., 2015		x	x			x																						
Seabrooke et al. 2003		x	x	x		x							x			x								x		x		x
Tian et al. 2013	x	x	x													x												
Tsai and Huang, 2015		x	x			x								x						x								
Van Dorsser et al. 2012						x										x												
Other Forecasting Studies																												
Engelen et al. 2007										x	x								x				x				x	
Kagkarakis et al. 2016	x							x				x																
Lee at al. 2017		x	x													x												
Tambakis, 1984		x				x							x		x			x										
Tsolakis et al. 2003										x	x												x				x	
Syriopoulos et al. 2021										x																		
FREQUENCY VALUE/53	9	20	15	8	2	23	5	7	4	13	8	9	12	6	6	10	7	8	3	3	2	4	7	2	2	6	5	2

forecasting. Du et al. (2019) applied VMD for pre-processing, BELM for optimization and error correction to the ensemble. Similarly, Xie et al. (2019) used the combinations of these three hybrid models. Chen et al. (2020) applied a hybrid decomposition ensemble method based on EMD, grey wave and ARMA for forecasting CCFI.

3. FORECASTING THEMES IN SHIPPING

Forecasting studies in shipping were classified into eight categories using their subjects as following: seaborne trade forecasts, average haul forecasts, ship demand forecasts, merchant fleet forecasts, ship productivity forecasts, freight rate forecasts (Stopford, 2009), port/terminal traffic forecasts, other shipping forecasts.

3.1. SEABORNE TRADE FORECAST

Seaborne trade forecasting is particularly guided to issues as planning, design, supervision, maritime safety (Feng et al. 2011), economic cooperation development, construction and renovation (Li et al. 2015), traffic control (Lv et al. 2016). Forecasting seaborne trade is a complex nonlinear dynamic process, nevertheless, a variety of models have been developed to describe this issue (Li et al. 2015). A simpler model (1) is revealed in the following regression model which indicates a linear relationship between GDP and seaborne trade (Stopford, 2009):

$$ST_t = f(GDP_t) \tag{1}$$

Similarly, UNCTAD (2016) estimated the seaborne trade volume based on the preliminary data. However, such simple models consist of the problem of continuity (Stopford, 2009). Similarly, related publications generally adopted simpler models and focused on specific regions. Moreover, both qualitative and quantitative forecasting techniques are preferred with different models.

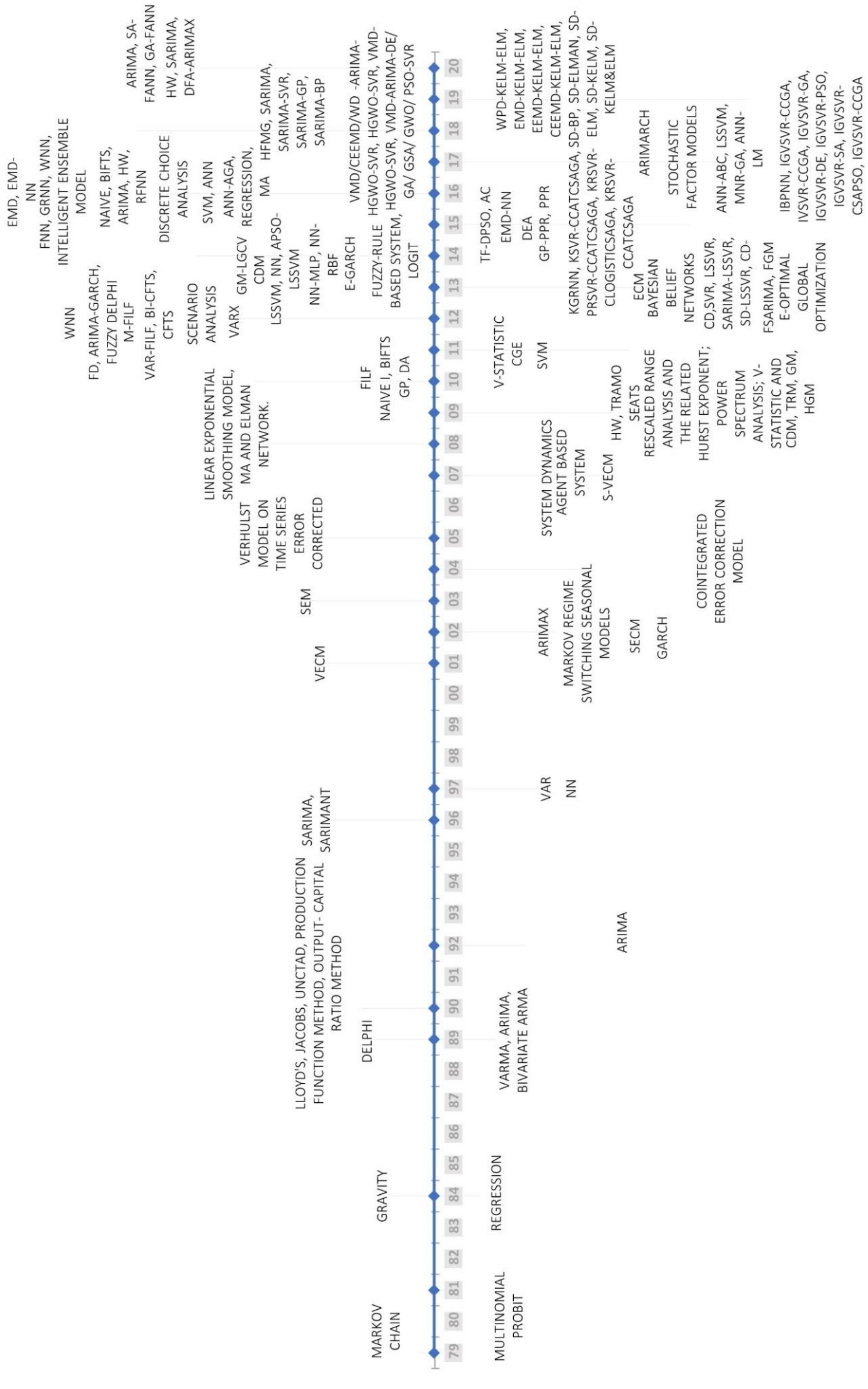

Figure 1. The Timeline of The Forecasting Methods Used in Shipping

3.2. AVERAGE HAUL FORECAST

Besides the volume, the distance over which the cargo is shipped also has an influencing factor of seaborne trade. Some routes generate more demand for seaborne trade and this distance effect is referred to as average haul (Lun et al. 2010). The average haul is estimated through historic trends or trade matrixes (Stopford, 2009). Clarksons Research (Crowe, 2016) has estimated the average haul for specific commodities. Kim (2013) mentioned the average haul forecasting of Capesize carriers. Thien (2005) forecasted average haul based on the annual data of dry bulk cargoes using the moving averages method and presented ex-post in sample and ex-ante forecasts.

3.3. SHIP DEMAND FORECAST

Ship demand is explained as the number of ships required to serve (Dumontier et al. 2016). Ship demand is one of the principal demand variables of seaborne trade and is referred to as the tonnages of cargo transported in a mile. It is bound to several factors such as price, speed, reliability, and security, which thus derives the vulnerability to change miles (Stopford, 2009). Stopford (2007) forecasted that ship demand increases from 1 billion dwt to 3.7 billion dwt in 2055.

3.4. MERCHANT FLEET FORECAST

One of the principal supply variables of seaborne transport is the merchant fleet which also compromises scrapping, deliveries, conversions, losses and removals (Stopford, 2009). The related literature review presents that researchers tend to avoid using complex forecasting techniques while forecasting the merchant fleet. Three of these studies used qualitative techniques. In terms of the forecasting exercise, ex-ante was employed by six of the studies.

3.5. SHIP PRODUCTIVITY FORECAST

Ship productivity is a dimension of the efficiency of the seaborne trade (Wing, 1973) and quantifies overall cargo carrying performance (Stopford, 2009). Specifically, ship productivity is the number of tons of cargo delivered by a ship in a year (Kovatch et al. 1971). Route length, ship speed and capacity, downtime, time spent in ballast, and turnaround time are the affecting measures for ship productivity (Wing, 1973). Crowe (2015) explained productivity as dividing tonnes of a trade by dwt fleet capacity to the average tonnes of cargo moved per dwt (in a year).

Forecast of this productivity ratio presented as well for world cargo fleet, bulk carriers, tankers, and containerships. UNCTAD (2006) also provided an estimation for the productivity of tankers, bulk carriers, and the residual fleet. Future projection of ship productivity is simply made by statistical series or more detailed methodology as stated in equation (2) (Stopford, 2009) where S is the average operating speed per hour, LD is the number of loaded days at sea per annum, and DWU is deadweight utilization:

$$P_{tm} = 24 \times S_{tm} \times LD_{tm} \times DWU_{tm} \quad (2)$$

3.6. FREIGHT RATE FORECAST

Due to the uncertainty and volatility in shipping pricing the shipping market and price behaviour of freight rates have attracted much interest in the shipping industry (Chen et al. 2012). Forecasting shipping freight is crucial for the shipping ecosystem as ship management companies, charterers (Duru 2010). Besides transport planning, ship financing, pricing of the finished goods; forecasting freight rates also affected shipping-related industries. Freight rate forecasting studies mostly concentrated on econometric modelling, simultaneous equations model and time series methods (Duru, 2010). After all, researchers seek to increase the accuracy of the forecasts and present more liable models (e.g., Cullinane, 1992; Chen et al. 2012; Eslami et al. 2016; Zeng et al. 2016).

Previous literature presented that freight rate forecasting literature generally focused on the tanker and dry bulk markets; the container market has been relatively paid less attention (Nielsen et al. 2014). However, reviewed literature suggests that freight rate prediction studies mostly focus on the dry bulk market rather than the tanker and container market in shipping. Most of the studies under review focus on freight rate index forecasting and generally dry bulk indices. Additionally, Santos et al. (2014) suggested that the forecasting spot freight market has paid more attention than period charter. Throughout the review, it is found that studies based on time/period charter have paid similar and even more attention than the spot charter. Moreover, a considerable amount of forward freight forecasting studies was also encountered.

3.7. PORT THROUGHPUT FORECAST

Port throughput forecast generally comprehends a forecasting model designed by the historical data (Liu et al. 2014) and provides a plan of the quantity, type, and structure of cargo. Successful port management developed from the balance between supply and demand as well as the conflict between them causes several difficulties as lack of modernization and conversion (Jugović et al. 2011), sunk cost of port construction (Chen and Chen, 2010), loss of efficiency in the port, failure of investment policy (Chu, 1979), failure of formulating appropriate strategies (Farhan and Ong. 2016). Therefore, port throughput forecasting is regarded as one of the most important basis of port planning, and constitutes a very complicated process because of the specific design of each port (Liu et al. 2014); perishability of the port services; the need for a large amount of data; continuous monitoring of port traffic, capacity, foreign exchange, GDP values; changes in the market of the state of which the port is part of, and transit countries; the changes in technology; the change in the movement of commodity flows (Jugović et al. 2011). Liu et al. (2014) claimed that most of the studies on port throughput are interested in container throughput and reviewed literature affirms this assessment as well as non-containerized cargo forecasting at ports merely encountered in the literature.

Moreover, only a few studies on port traffic forecasting have been published before 2000, most of the encountered studies were published after 2000. These studies used a variety of methods to forecast port traffic including time series, econometric, soft computing, statistical and judgmental methods, and forecasting competition is preferred by most of the researchers to find the appropriate model to forecast. In terms of the region focused, Hong Kong (8) and Shanghai (8) are mostly researched ports as forecasting handled cargo volumes.

3.8. OTHER FORECASTING STUDIES

Except for the above-categorized topics, forecasting in shipping also includes issues related to shipping finance, port and ship operations, and traffic management, shipping marketing and shipping economics. Studies related to shipping finance present forecasting newbuilding, second-hand and demolition prices and costs, oil spill costs, shipping cycles, shipping receipts, credit flows, excess returns, and risk. Port and ship operations and traffic management related studies focus on predicting arrival and dwell times, the inspections and safety/detention performance, vessel type and volume traffic, route of the future. Additionally, marketing and economics related forecasting in shipping indicate forecasting demand for shipping business and future market share.

4. FUTURE RESEARCH AGENDA

Based on the previous findings, more research is needed to find out consistently accurate models across different forecasting shipping situations. First, future research could consider focusing on a broader geographical area in terms of seaborne trade forecast.

This review reveals that most of the forecasting models use monthly data. We propose that future studies can explore the cases which increase accuracy including forecast horizon, data frequency, and the number of observations. Although Nielsen et al. (2014) pointed out this interaction, the question of how to design and choose the superior model in terms of the forecast horizon, data frequency, and the number of observations and their interactions is still missing.

Along with the shipping and transportation journals, port traffic forecasting studies in shipping have been published in mathematics and computing journals while freight rate forecasting studies have been published in econometrics journals. Therefore, it is noticeable that used data while developing forecasting models in shipping is suitable for developing detailed and complex models. This finding confirms Hajirahimi and Khashei (2019) that port throughput studies are one of the most preferred fields on hybrid time series forecasting.

Most of the developed forecasting models are based on seasonality characteristics. However, each data should be searched for seasonality components and the nature of the seasonality before developing the models. Moreover, more empirical research is needed to clarify the nature of the seasonality in shipping markets

Volatility is a significant index to measure risk and the variability of the shipping market is often higher than that of the financial markets (Liu et al. 2021). Hence, there is a growing literature on the volatility of the shipping markets. Despite the existence of the studies focusing on freight rate volatility, port traffic volatility should be focused on as well. This research gap was also suggested by Notteboom et al. (2019). Although some researchers are investigating the moderating roles in volatility forecasting (e.g. Gavriilidis et al. (2018)), further researches could pursue the expansion by identifying new moderator variables. Even though some of the studies (e.g. Bekes et al. 2017, Liu et al. 2021) have attempted to focus on using alternative measures of volatility, more focus should be given towards different volatility measures.

Cyclicality is another critical data characteristic and there are many researches investigating cyclicality in shipping. However, the findings of these have pointed out different cycles and, further investigation on cyclicality in shipping for different market segments with different methods would contribute to the literature. Furthermore, as proposed by Siddiqui and Basu (2020) the future studies can further focus on the influencing factors of various cycles. The key in shipping forecasts will be the data characteristics analysis, and each research specifically should focus on a data characteristics analysis before developing forecasting models in shipping.

Reviewed studies show that there is a need to clarify the effects of data aggregation on forecasting studies. While forecasting shipping prices (freight rates, ship prices, etc), forecasting models should be developed and benchmarked considering segments of the markets such as ship size, container category, destination, customer zone. While forecasting shipping volumes (port throughput, demolition volumes, etc.), more research is needed to straighten the results of Pang and Gebka (2017). Further research in this respect is required.

According to Table 1, recent studies have increasingly tended to include more explanatory variables. It will be critical to explore which set of variables should a model includes in certain forecasting cases. For empirical studies having feature selection sections will be critical to increase the accuracy of the developed models. We propose that evolutionary algorithms can be used in this respect, and the studies can focus on finding the appropriate feature selection.

Finally, it is clear from the reviewed studies that developed models have tended to become more complex over time. Several hybrid models are proposed in shipping literature. Zhou and Zhao (2016) and Li et al (2008) used nonlinear combination, Mo et al. (2018), and Niu et al. (2018) used linear-nonlinear combination. We can identify that more empirical research will be conducted on decomposition-ensemble models and optimization of the nonlinear part. Alongside this, nonlinear-linear models should be considered for further research.

Although the broad usage of quantitative methods in the forecasting shipping industry, qualitative methods are neglected, and additional efforts need to be made in this regard. New attempts should be made to further enhance forecast accuracy by combining forecasts both quantitatively and qualitatively.

Finally, there is a research gap on the relationships between the accuracy of forecasting models and forecasting cases (e.g. data characteristics and features), the influence of these characteristics can contribute to shipping forecast literature.

5. IMPLICATIONS TO INDUSTRY AND CONCLUSIONS

Deciding on the proper forecasting method could be challenging for the practitioners. This review assists the shipping industry stakeholders in decision making for forecasting methodology. Therefore, more effective policies and decisions might be reached. This paper also reveals the state of the art of related variables. Hence, it can be useful for practitioners while developing forecasts in shipping markets. As stated earlier, due to the complex nature of the shipping industry shipping forecasts need to be combined using qualitative and quantitative methods. This forecasting combination strategy rather than the forecast competition can be an advantage for practitioners to reach more accurate forecasts.

Considering the forecasting of unexpected circumstances such as crises, events or actions has not gained much attention in the literature. Forecasting and modelling these circumstances, their potential impacts, and causes will be critical to explore further in future research.

The important point extracted from the evaluation of the forecasting methods is that there is no research about the proper metrics for forecasting shipping cases. Research in the proper evaluation of the forecasting shipping cases and guidelines should be stated by researchers.

Forecasting in shipping has great significance both to academic research and to practice. Based on the findings of this paper, we have presented a future research agenda and implications to the industry intending to encourage more research into forecasting in shipping. Although we attempted to investigate accurately and carefully as possible, there are some limitations as follows: (1) This paper covered 161 papers published on shipping forecasting models, there are some studies that were overlooked unintentionally during the data retrieval process. (2) In this review we characterized the shipping forecast themes and presented summaries for each theme, the investigation could be deepened for each theme. (3) It should be noted that turning points, directional changes, events' impacts, and risk forecasting are not specifically pointed out in this review, and these issues shall be covered in future studies. (4) Oceanographic, navigational, meteorological forecasting studies have been considered out of scope in the context of this paper.

The importance of forecasting in shipping markets can be observed from the existing broad literature on the issue. There are many attempts to provide more accurate and reliable forecasts to enlighten the shipping industry for decision and policy-making purposes. This paper reveals the state of the art and identifies some research gaps and problems for this topic. By reviewing studies, forecasting themes, variables, data characteristics models and methods have been investigated. The reviewed studies clearly showed that developed models have tended to become more complex over time. Although hybrid models tend to increase the accuracy of the forecasts, no consensus has been reached on the type of forecasting models that perform more accurately in specific forecasting cases. New attempts should be encouraged to further enhance the forecasting accuracy through data decompositions, explanatory data inclusions, hybrid model developments, and qualitative and quantitative forecast combinations.

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7. REFERENCES

1. ADLAND, R. and CULLINANE, K. (2006). The non-linear dynamics of spot freight rates in tanker markets. *Transportation Research Part E: Logistics and Transportation Review,* 42(3), 211-224.
2. ALIZADEH, A. H., ÅDLAND, R. O. et al. (2007). Predictive Power and Unbiasedness of Implied Forward Charter Rates. *Journal of Forecasting,* 26(6): 385-403.
3. ALIZADEH, A. H. and NOMIKOS, N. K. (2011). Dynamics of the term structure and volatility of shipping freight rates. *Journal of Transport Economics and Policy,* 45(1), 105-128.
4. ARIEL, A. (1989). Delphi forecast of the Dry Bulk Shipping Industry in The Year 2000.

Maritime Policy and Management, 16(4): 305-336.

5. BABCOCK, M. W. and LU, X. (2002). Forecasting Inland Waterway Grain Traffic. *Transportation Research Part E: Logistics and Transportation Review*, 38(1): 65-74.
6. BAO, J., PAN, L. et al. (2016). A New BDI Forecasting Model Based on Support Vector Machine. In 2016 *IEEE Information Technology, Networking, Electronic and Automation Control Conference* (pp. 65-69), 20-22 May 2016.
7. BEENSTOCK, M. and VERGOTTIS, A. (1993). *Econometric Modelling of World Shipping.* Springer Science and Business Media.
8. BEKES, G., FONTAGNE, L., et al. (2017). Shipment frequency of exporters and demand uncertainty. *Review of World Economics*, 153(4), 779-807.
9. CHANG, C. C., HSIEH, C. Y. et al. (2012). *A Predictive Model of The Freight Rate of The International Market in Capesize Dry Bulk Carriers.* Applied Economics Letters, 19(4): 313-317.
10. CHAREMZA, W. and GRONICKI, M. (1981). *An Econometric Model of World Shipping and Shipbuilding.* Maritime Policy and Management, 8(1): 21-30.
11. CHEN, S. H. and CHEN, J. N. (2010). *Forecasting Container Throughputs at Ports Using Genetic Programming.* Expert Systems with Applications, 37(3): 2054-2058.
12. CHEN, Y., LIU, B. et al. (2020). *Analysing and forecasting China containerized freight index with a hybrid decomposition–ensemble method based on EMD, grey wave and ARMA.* Grey Systems: Theory and Application.
13. CHEN, S., MEERSMAN, H. et al. (2012). *Forecasting Spot Rates at Main Routes in The Dry Bulk Market.* Maritime Economics and Logistics, 14(4): 498-537.
14. CHEN, Y. S. and WANG, S. T. (2004). The empirical evidence of the leverage effect on volatility in international bulk shipping market. *Maritime Policy & Management*, 31(2), 109-124.
15. CHEN, J., XUE, K., SONG, et al. (2019). *Periodicity of world crude oil maritime transportation: Case analysis of Aframax Tanker market.* Energy Strategy Reviews, 25, 47-55.
16. CHISTÈ, C. and VAN VUUREN, G. (2014). Investigating the cyclical behaviour of the dry bulk shipping market. Maritime Policy & Management, 41(1), 1-19.
17. CHOW, J. Y., YANG, C. H., et al. (2010). State-of-the Art of Freight Forecast Modeling: Lessons Learned and The Road Ahead. Transportation. 37(6): 1011-1030.
18. CHU, D. K. Y. (1979). *The Foreign Non-Fuel Cargo-Traffic Demand of the Major British Seaports in 1980 And 1985, A Markov Chain Approach.* Maritime Policy and Management, 6(4): 293-303.
19. CLAESSENS, E. M., KAMEL, M., et al. (1984). *Traffic and Trade Projections on the Eastbound Suez Shipping Route.* Maritime Policy and Management, 11(1): 45-55.
20. COOPER, H. M. (1982). *Scientific Guidelines for Conducting Integrative Research Reviews.* Review of Educational Research, 52(2), 291-302.
21. COTO-MILLÁN, P., CASARES-HONTAÑÓN, P. et al. (2013). *Demand for Port Traffic by Type of Good in Spain: 1995 I - 2007 IV.* Maritime Economics and Logistics, 15(4): 444-466.
22. CROWE, T. (2015). *Driving Productivity - But Which Way?* Clarkson Research. https://sin.clarksons.net/features/Details/36397. (Accessed 24 April 2017).
23. CROWE, T. (2016). *In It for the Long-Haul and the Short Haul Too.* Clarkson Research. https://sin.clarksons.net/features/Details/40759. (Accessed 18 April 2017).
24. DE GOOIJER, J. G., and KLEIN, A. (1989). *Forecasting the Antwerp Maritime Steel Traffic Flow: A Case Study.* Journal of Forecasting, 8(4): 381-398.
25. DE LANGEN, P. W. (2003). *Forecasting Container Throughput, a Method Implication for Port Planning.* Journal of International Logistics and Trade, 1 (1): 29-39.
26. DENNING, K. C., RILEY, W. B. et al. (1994). *Baltic freight futures: Random walk or seasonally predictable?* International Review of Economics & Finance, 3(4), 399-428.
27. DRAGAN, D., KESHAVARZSALEH, A. et al. (2020). *Throughput Forecasting of Different Types of Cargo in the Adriatic Seaport Koper.* Maritime Policy & Management, 1-27.
28. DROBETZ, W., RICHTER, T. et al. (2012). *Dynamics of the time-varying volatility in the dry bulk and tanker freight markets.* Applied Financial Economics, 22, 1367–1384
29. DU, P., WANG, J., et al. (2019). *Container throughput forecasting using a novel hybrid learning method with error correction strategy.* Knowledge-Based Systems, 182, 104853.
30. DUMONTIER, M, BROWN, D. et al. (2016). *Optimizing LNG Shipping Portfolios: Realities, Uncertainties, Opportunities*. 18th International Conference and Exhibition on Liquefied Natural Gas. 11-15 April 2016, Australia.
31. ENGELEN, S., DULLAERT, W. et al. (2007). *Multi-agent adaptive systems in dry bulk shipping.* Transportation Planning and Technology, 30(4): 377-389.
32. ERDOGAN, O. and SENGOZ, M.H. (2007). *Forecasting World Fleet: Issues for Greek and Turkish Fleet.* Journal of Transport and Shipping, (4): 41-52.

33. ESLAMI, P., JUNG, K., et al. (2016). *Predicting Tanker Freight Rates Using Parsimonious Variables and A Hybrid Artificial Neural Network with an Adaptive Genetic Algorithm.* Maritime Economics and Logistics,19(3): 538-550.
34. FARHAN, J., and ONG, G. P. (2016). *Forecasting Seasonal Container Throughput at International Ports Using SARIMA Models.* Maritime Economics and Logistics, 20(1): 131-148.
35. FEI, Y., CHEN, J. et al. (2020). *Crude Oil Maritime Transportation: Market Fluctuation Characteristics and the Impact of Critical Events.* Energy Reports, 6, 518-529.
36. FENG, H., KONG, F., et al. (2011). *Vessel Traffic Flow Forecasting Model Study Based on Support Vector Machine.* In International Conference on Electronic Commerce, Web Application, and Communication (pp. 446-451). Berlin: Springer.
37. FUNG, K. F. (2001). *Competition Between the Ports of Hong Kong and Singapore: A Structural Vector Error Correction Model to Forecast the Demand for Container Handling Services.* Maritime Policy and Management, 28(1): 3-22.
38. FUNG, M. K. (2002). *Forecasting Hong Kong's Container Throughput: An Error-Correction Model.* Journal of Forecasting, 21(1): 69-80.
39. GAVRIILIDIS, K., D. KAMBOUROUDIS, K. et al. (2018). *Volatility forecasting across tanker freight rates: The role of oil price shocks.* Transportation Research Part E-Logistics and Transportation Review, 118: 376–391.
40. GENG, J., LI, M. W. et al. (2015). *Port Throughput Forecasting By MARS-RSVR With Chaotic Simulated Annealing Particle Swarm Optimization Algorithm.* Neurocomputing, 147: 239-250.
41. GEOMELOS, N. D., and XIDEAS, E. (2014). *Forecasting Spot Prices in Bulk Shipping Using Multivariate and Univariate Models.* Cogent Economics and Finance, 2(1): 923701.
42. GOSASANG, V., CHANDRAPRAKAIKUL, W. et al. (2010). *An Application of Neural Networks for Forecasting Container Throughput at Bangkok Port.* In 12th World Congress on Transportation Research. 30.06 – 02.07. 2010. London.
43. GOULIELMOS, A. M. and PSIFIA, M. E. (2009). *Forecasting Weekly Freight Rates for One-Year Time Charter 65 000 Dwt Bulk Carrier, 1989–2008, Using Nonlinear Methods.* Maritime Policy and Management, 36(5): 411-436.
44. GOKKUŞ, U., YILDIRIM, et al. (2017). Estimation of container traffic at seaports by using several soft computing methods: a case of Turkish Seaports. Discrete Dynamics in Nature and Society, 2017.
45. HAJIRAHIMI, Z., and KHASHEI, M. (2019). *Hybrid Structures in Time Series Modelling and Forecasting: A Review.* Engineering Applications of Artificial Intelligence, 86, 83-106.
46. HSIAO, Y. J., CHOU, H. C. et al. (2014). *Return Lead–Lag and Volatility Transmission in Shipping Freight Markets.* Maritime Policy & Management. 41(7): 697-714.
47. HSU, C. I., HUANG, Y. C. et al. (2020). A Grey hybrid model with industry share for the forecasting of cargo volumes and dynamic industrial changes. *Transportation Letters.* 12(1), 25-36.
48. HUANG, A., LAI, K. et al. (2015). *Forecasting Container Throughput of Qingdao Port with A Hybrid Model.* Journal of Systems Science and Complexity, 28(1): 105-121.
49. HUI, E. C., SEABROOKE, W. et al. (2004). *Forecasting Cargo Throughput for The Port of Hong Kong: Error Correction Model Approach.* Journal of Urban Planning and Development, 130(4): 195-203.
50. HYLLEBERG, S., ENGLE, R. F. et al. (1990). Seasonal Integration and Cointegration. *Journal of Econometrics*, 44(1-2), 215-238.
51. HYNDMAN, R.J., and ATHANASOPOULOS, G. (2018) Forecasting: principles and practice, 2nd edition, OTexts: Melbourne, Australia. OTexts.com/fpp2. (Accessed on 08 June 2021)
52. JEON, J., DURU, O. et al. (2020) *Modelling cyclic container freight index using system dynamics.* Maritime Policy & Management, 47(3), 287-303.
53. JING, L., MARLOW, P. B. et al. (2008). *An analysis of freight rate volatility in dry bulk shipping markets.* Maritime Policy & Management, 35(3), 237-251.
54. JONNALA, S., FULLER, S. et al. (2002*). A GARCH Approach to Modelling Ocean Grain Freight Rates.* International Journal of Maritime Economics, 4(2): 103-125.
55. JUGOVIĆ, A., HESS, S. et al. (2011). *Traffic Demand Forecasting for Port Services.* PROMET-Traffic and Transportation, 23(1): 59-69.
56. KAGKARAKIS, N. D., MERIKAS, A. G. et al. (2016). *Modelling and Forecasting the Demolition Market in Shipping.* Maritime Policy and Management, 43(8): 1021-1035.
57. KAVUSSANOS, M. G. (1996). *Comparisons of Volatility in the Dry-Cargo Ship Sector: Spot Versus Time Charters, and Smaller Versus Larger Vessels.* Journal of Transport Economics and Policy, 67-82.
58. KAVUSSANOS, M. G. and ALIZADEH-M, A. H. (2001). *Seasonality Patterns in Dry Bulk Shipping Spot and Time Charter Freight Rates*. Transportation Research Part E: Logistics and Transportation Review, 37(6), 443-467.

59. KAVUSSANOS, M. G. and ALIZADEH-M, A. H. (2002a). *Seasonality Patterns in Tanker Spot Freight Rate Markets.* Economic Modelling, 19(5), 747-782.
60. KAVUSSANOS, M. G. and ALIZADEH, A. H. (2002b). *Efficient Pricing of Ships in The Dry Bulk Sector of the Shipping Industry*. Maritime Policy and Management, 29(3): 303-330.
61. KIM, K. H. (2013). *Forecasting the Capesize Freight Market*. Unpublished Master's Thesis. World Maritime University. Shipping and Port Management. Sweden.
62. KLEIN, A. (1996). *Forecasting the Antwerp Maritime Traffic Flows Using Transformations and Intervention Models.* Journal of Forecasting, 15(5): 395-412.
63. KOVATCH, G., BARBER, J. B. et al. (1971). *Transportation Systems Technology: A Twenty-Year Outlook* (No. DOT-TSC-OST-71-10 Final Rpt). United States. Dept. of Transportation. Office of the Secretary.
64. KRANTZ, R., SØGAARD, K. et al. (2020). *The Scale of Investment Needed to Decarbonize International Shipping.* In Getting to Zero Coalition Insight Series. Global Maritime Forum, Friends of Ocean Action, and World Economic Forum. <https://www.globalmaritimeforum.org/content/2020/01/Getting-to-Zero-Coalition_Insight-brief_Scale-of-investment. pdf.> (Accessed on 1 December 2020).
65. LAM, W. H., NG, P. L. et al. (2004). *Forecasts and Reliability Analysis of Port Cargo Throughput in Hong Kong.* Journal of Urban Planning and Development, 130(3): 133-144.
66. LAUENSTEIN, P. and WALTHER, T. (2016). *Forecasting Volatility of Tanker Freight Rates Based on Asymmetric Regime Switching GARCH Models.* International Journal of Financial Engineering and Risk Management, 2(3), 172-199.
67. LEE, S. Y., LIM, H. et al. (2017). *Forecasting Container Port Volume: Implications for Dredging.* Maritime Economics and Logistics, 19(2): 296-314.
68. LEONOV, Y. and NIKOLOV, V. (2012). *A Wavelet and Neural Network Model for The Prediction of Dry Bulk Shipping Indices.* Maritime Economics and Logistics, 14(3): 319-333.
69. LI, H., BAI, J. et al. (2019). *A Novel Secondary Decomposition Learning Paradigm with Kernel Extreme Learning Machine for Multi-Step Forecasting of Container Throughput.* Physica A: Statistical Mechanics and its Applications, 534, 122025.
70. LI, J., CHEN, Y. et al. (2008). *Port Throughput Forecast Based on Nonlinear Combination Method.* Eds. Q. Li, S. Y. Chen, and A. Xu. In *WSEAS International Conference.* Proceedings. Mathematics and Computers in Science and Engineering (No. 7). World Scientific and Engineering Academy and Society. 6-8 April 2008.
71. LI, W., DAI, J. et al. (2020). *Estimating Waterway Freight Demand at Three Gorges Ship Lock on Yangtze River by Backpropagation Neural Network Modeling.* Maritime Economics & Logistics, 1-27.
72. LI, M. W., GENG, J. et al. (2017). *A Novel Approach Based on the Gauss-VSVR With A New Hybrid Evolutionary Algorithm and Input Vector Decision Method for Port Throughput Forecasting.* Neural Computing and Applications, 28(1), 621-640.
73. LI, M., HAN, D. et al. (2015). *Vessel Traffic Flow Forecasting by RSVR with Chaotic Cloud Simulated Annealing Genetic Algorithm and KPCA.* Neurocomputing, 157: 243-255.
74. LI, J. and PARSONS, M. G. (1997). *Forecasting Tanker Freight Rate Using Neural Networks.* Maritime Policy and Management. 24(1): 9-30.
75. LI, T., XUE, L. et al. (2018). *Insights from Multifractality Analysis of Tanker Freight Market Volatility with Common External Factor of Crude Oil Price.* Physica A: Statistical Mechanics and its Applications, 505, 374-384.
76. LIU, J., LI, Z. et al. (2021). Volatility forecasting for the shipping market indexes: an AR-SVR-GARCH approach. Maritime Policy & Management, 1-18.
77. LIU, S., TIAN, L., et al. (2014). *A Comparative Study on Prediction of Throughput in Coal Ports Among Three Models.* International Journal of Machine Learning and Cybernetics. 5(1): 125-133.
78. LUN, Y. V., LAI, K. H. et al. (2010). *Shipping and Logistics Management*. London: Springer.
79. LUN, Y. V., and QUADDUS, M. A. (2009). An empirical model of the bulk shipping market. *International Journal of Shipping and Transport Logistics*. 1(1), 37-54.
80. LUO, M., FAN, L. et al. (2009). *An Econometric Analysis for Container Shipping Market.* Maritime Policy and Management, 36(6): 507-523.
81. LV, P., ZHUANG, Y. et al. (2016). *Prediction of Ship Traffic Flow Based on BP Neural Network and Markov Model.* ICTTE 2016 in MATEC Web of Conferences.81: 1-5.
82. LYK-JENSEN, S. V. (2011). *Forecasting Freight Flows.* Transport Reviews, 31(5): 603-624.
83. LYRIDIS, D. V., ZACHARIOUDAKIS, P. et al. (2004). *Forecasting Tanker Market Using Artificial Neural Networks*. Maritime Economics and Logistics, 6(2): 93-108.
84. LYRIDIS, D., ZACHARIOUDAKIS, P. et al. (2013). *Freight-Forward Agreement Time Series Modelling Based on Artificial Neural Network*

Models. Strojniski Vestnik-Journal of Mechanical Engineering, 59(9): 511-518.

85. MO, L., XIE, L. et al. (2018). *GMDH-based hybrid model for container throughput forecasting: Selective combination forecasting in nonlinear subseries.* Applied Soft Computing, 62, 478-490.

86. MOSTAFA, M. M. (2004*). Forecasting the Suez Canal Traffic: A Neural Network Analysis.* Maritime Policy and Management, 31(2): 139-156.

87. MUNIM, Z. H. and SCHRAMM, H. J. (2017). *Forecasting Container Shipping Freight Rates for The Far East–Northern Europe Trade Lane.* Maritime Economics and Logistics, 19(1): 106-125.

88. MUNIM, Z. H. and SCHRAMM, H. J. (2020). *Forecasting Container Freight Rates for Major Trade Routes: A Comparison of Artificial Neural Networks and Conventional Models.* Maritime Economics & Logistics, 1-18.

89. NIELSEN, P., JIANG, L. et al. (2014). *An Investigation of Forecast Horizon and Observation Fit's Influence on an Econometric Rate Forecast Model in The Liner Shipping Industry.* Maritime Policy and Management, 41(7): 667-682.

90. NIU, M., HU, Y. et al. (2018). *A Novel Hybrid Decomposition-Ensemble Model Based on VMD And HGWO for Container Throughput Forecasting.* Applied Mathematical Modelling, 57, 163-178.

91. NOTTEBOOM, T. E., PAROLA, F. et al. (2019). The relationship between transhipment incidence and throughput volatility in North European and Mediterranean container ports. *Journal of Transport Geography*, 74 (2019), 371-381.

92. PANG, G. and GEBKA, B. (2017). *Forecasting Container Throughput Using Aggregate or Terminal-Specific Data? The Case of Tanjung Priok Port, Indonesia.* International Journal of Production Research. 55(9): 2454-2469.

93. PAPAILIAS, F., THOMAKOS, D. D. et al. (2017). *The Baltic Dry Index: Cyclicalities, Forecasting and Hedging Strategies.* Empirical Economics. 52(1): 255-282.

94. PAROLA, F., SATTA, G. (2020). *Revisiting Traffic Forecasting by Port Authorities in The Context of Port Planning and Development.* Maritime Economics & Logistics. 1-51.

95. 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. 20(5): 2022-2032.

96. PATIL, G. R. and SAHU, P. K. (2017). *Simultaneous Dynamic Demand Estimation Models for Major Seaports in India.* Transportation Letters. 9(3): 141-151.

97. PENG, W. Y. and CHU, C. W. (2009). *A Comparison of Univariate Methods for Forecasting Container Throughput Volumes.* Mathematical and Computer Modelling. 50(7): 1045-1057.

98. POBLACION, J. (2015). *The Stochastic Seasonal Behaviour of Freight Rate Dynamics.* Maritime Economics & Logistics, 17(2), 142-162.

99. RANDERS, J., and GÖLUKE, U. (2007). *Forecasting Turning Points in Shipping Freight Rates: Lessons from 30 Years of Practical Effort.* System Dynamics Review: The Journal of the System Dynamics Society, 23(2-3): 253-284.

100. RASHED, Y., MEERSMAN, H. et al. (2017). *Short-Term Forecast of Container Throughout: An ARIMA-Intervention Model for The Port of Antwerp.* Maritime Economics and Logistics, 19(4): 749-764.

101. RASHED, Y., MEERSMAN, H. et al. (2018). *A combined approach to forecast container throughput demand: Scenarios for the Hamburg-Le Havre range of ports.* Transportation Research Part A: Policy and Practice. 117: 127-141.

102. RUIZ-AGUILAR, J. J., TURIAS, I. J. et al. (2014). *Hybrid Approaches of Support Vector Regression and SARIMA Models to Forecast the Inspections Volume.* In International Conference on Hybrid Artificial Intelligence Systems (pp. 502-514). Springer International Publishing.

103. SAHU, P. K. and PATIL, G. R. (2015). *Handling Short Run Disequilibrium in Freight Demand Forecasting at Major Indian Ports Using Error Correction Approach.* European Transport-Trasporti Europei. (59).

104. SANTOS, A. A., JUNKES, L. N. et al. (2014). *Forecasting Period Charter Rates of VLCC Tankers Through Neural Networks: A Comparison of Alternative Approaches.* Maritime Economics and Logistics, 16(1): 72-91.

105. SATIR, T., DEMIR, H. et al. (2008). *Ship Waste Forecasting at The Botas LNG Port Using Artificial Neural Networks.* Fresenius Environmental Bulletin, 17(12A): 2064-2070.

106. SCHULZE, P. M. and PRINZ, A. (2009). *Forecasting Container Transshipment in Germany.* Applied Economics, 41(22): 2809-2815.

107. SEABROOKE, W., HUI, E. C. et al. (2003). *Forecasting Cargo Growth and Regional Role of the Port of Hong Kong.* Cities, 20(1): 51-64.

108. SHANKAR, S., ILAVARASAN, P. V. et al. (2019). *Forecasting container throughput with long short-term memory networks.* Industrial Management & Data Systems, 120 (3): 425-441

109. SHU, M. H., HUANG, Y. F. et al. (2013). *Forecasting Models for the Cargo Throughput at Hong Kong Port and Kaohsiung Port.* Recent

Researches in Applied Economics and Management, Greece: WSEAS Press.

110. SIDDIQUI, A. W. and BASU, R. (2020). *An Empirical Analysis of Relationships Between Cyclical Components of Oil Price and Tanker Freight Rates.* Energy, 117494.

111. SOLAK-FISKIN, C. (2020*). Domestic Dry Cargo Shipping Market: Using Models to Develop Forecasts.* PhD thesis, Dokuz Eylul University, Izmir. Available at : *https://tez.yok.gov.tr/UlusalTezMerkezi/giris.jsp*

112. SONG, H. and LI, G. (2008). *Tourism Demand Modelling and Forecasting—A Review of Recent Research.* Tourism Management, 29(2), 203-220.

113. STOPFORD, M. (2007). *Will the next 50 years be as Chaotic in Shipping as the Last?* Hong Kong Shipowners Association, 50th Anniversary Analyst's lunch, 18th January 2007.

114. STOPFORD, M. (2009). *Maritime Economics.* 3e. Routledge.

115. SUN, L. (2010). *The Research on a Double Forecasting Model of Port Cargo Throughput.* World Journal of Modelling and Simulation. 6: 57-62.

116. SUN, X., TANG, L. et al. (2014). *Identifying the Dynamic Relationship Between Tanker Freight Rates and Oil Prices: In the Perspective of Multiscale Relevance.* Economic Modelling, 42, 287-295.

117. SYRIOPOULOS, T., TSATSARONIS, M. et al. (2021). *Support Vector Machine Algorithms: An Application to Ship Price Forecasting.* Computational Economics, 1-33.

118. TAMBAKIS, D. (1984*). An Econometric Analysis of the Factors Affecting Shipping in Greece.* Maritime Policy and Management, 11(1): 21-33.

119. TAVASSZY, L. A., RUIJGROK, K. et al. (2012). *Incorporating Logistics in Freight Transport Demand Models: State-Of-The-Art and Research Opportunities.* Transport Reviews. 32(2): 203-219.

120. THE GLOBAL INFRASTRUCTURE HUB. (2020). *Global Infrastructure Outlook - A G20 INITIATIVE.* <https://outlook.gihub.org/sectors/port> (Accessed on 1 December 2020).

121. THIEN, L.D. (2005). *Forecasting the Dry Bulk Freight Market*. Unpublished Master's Thesis. World Maritime University. Sweden.

122. TIAN, X., LIU, L. et al. (2013). *Analysis and Forecasting of Port Logistics Using TEI@ I Methodology*. Transportation Planning and Technology. 36(8): 685-702.

123. TINBERGEN, J. (1959). *Tonnage and Freight.* L.H. Klaassen L.M. Koyck and H.J. Witteveen (eds.) Jan Tingergen Selected Papers. Netherlands: North-Holland Publishing Company.

124. TONGZON, J. (1991). *A Model for Forecasting Future Supply of Shipping Services at Australian Ports.* Maritime Policy and Management, 18(1). 55-68.

125. TSAI, F. M., and HUANG, L. J. (2015). *Using Artificial Neural Networks to Predict Container Flows Between the Major Ports of Asia.* International Journal of Production Research, 1-10.

126. TSIOUMAS, V., S. PAPADIMITRIOU, Y. et al. (2017). *A novel approach to forecasting the bulk freight market.* Asian Journal of Shipping and Logistics, 33 (1): 33–41.

127. TSOLAKIS, S. D., CRIDLAND, C. et al. (2003). *Econometric Modelling of Second-Hand Ship Prices.* Maritime Economics and Logistics, 5(4): 347-377.

128. TSOUKNIDIS, D. A. (2016). *Dynamic Volatility Spillovers Across Shipping Freight Markets.* Transportation Research Part E: Logistics and Transportation Review. 91: 90-111.

129. UNCTAD. (2006). *Review of Maritime Transport*. New York and Genova.

130. UNCTAD. (2016). *Review of Maritime Transport*. New York and Genova.

131. UNCTAD. (2018). *Review of Maritime Transport*. New York.

132. UNCTAD. (2020). *Review of Maritime Transport*. New York.

133. VAN DORSSER, J. C. M., WOLTERS, M. et al. (2012). *A Very Long-Term Forecast of the Port Throughput in the Le Havre–Hamburg Range up to 2100.* EJTIR. 12(1): 88-110.

134. VEENSTRA, A.W. and FRANSES, P. H. (1997). *A Cointegration Approach to Forecasting Freight Rates in The Dry Bulk Shipping Sector.* Transportation Research. Part A: Policy and Practice, 31 (6): 447-458.

135. WADA, Y., HAMADA, K. et al. (2018*). A System Dynamics Model for Shipbuilding Demand Forecasting.* Journal of Marine Science and Technology, 23(2), 236-252.

136. WING, J. F. (1973). *Trends in World Shipping*. Conference Proceedings on Bulk Transportation of Hazardous Materials by Water in the Future: A Long-Range Forecast. Maryland. 9-10 July 1973.

137. WINSTON, C. (1981). *A Multinomial Probit Prediction of the Demand for Domestic Ocean Container Service.* Journal of Transport Economics and Policy, 243-252.

138. XIAO, Y., WANG, S. et al. (2016). *Throughput Estimation Based Port Development and Management Policies Analysis*. Maritime Policy and Management, 43(1): 84-97.

139. XIAO, J., XIAO, Y. et al. (2014). *A Transfer Forecasting Model for Container Throughput Guided by Discrete PSO.* Journal of Systems Science and Complexity. 27(1): 181-192.

140. XIE, G., QIAN, Y. et al. (2019). *Forecasting Container Throughput Based on Wavelet Transforms Within A Decomposition-Ensemble Methodology: A Case Study of China.* Maritime Policy & Management, 46(2), 178-200.
141. XIE, G., WANG, S. et al. (2013). *Hybrid Approaches Based on LSSVR Model for Container Throughput Forecasting: A Comparative Study.* Applied Soft Computing, 13(5): 2232-2241.
142. XIE, G., ZHANG, N. et al. (2017). *Data Characteristic Analysis and Model Selection for Container Throughput Forecasting Within A Decomposition-Ensemble Methodology.* Transportation Research Part E: Logistics and Transportation Review, 108, 160-178.
143. YANG, H., DONG, F. et al. (2008). *Forewarning of Freight Rate in Shipping Market Based on Support Vector Machine.* Sixth International Conference of Traffic and Transportation Studies Congress (ICTTS) (pp. 295-303).
144. YANG, Z. and MEHMED, E. E. (2019). *Artificial Neural Networks in Freight Rate Forecasting.* Maritime Economics & Logistics, 21(3), 390-414.
145. YIN, J. and SHI, J. (2018). *Seasonality Patterns in The Container Shipping Freight Rate Market.* Maritime Policy & Management, 45(2), 159-173.
146. YIN, J., WU, Y. et al. (2019). *Assessment of Investment Decision in the Dry Bulk Shipping Market Based on Real Options Thinking and the Shipping Cycle Perspective.* Maritime Policy & Management, 46(3), 330-343.
147. YONG HUI, F., XING, Y.W. et al. (2014). *Prediction of Baltic Capesize Freight Index Based on GARCH Model.* Applied Mechanics and Materials, 488-489: 1494-1497
148. ZENG, Q., and QU, C. (2014). *An Approach for Baltic Dry Index Analysis Based on Empirical Mode Decomposition.* Maritime Policy and Management, 41(3): 224-240.
149. ZENG, Q., QU, C. et al. (2016). *A New Approach for Baltic Dry Index Forecasting Based on Empirical Mode Decomposition and Neural Networks.* Maritime Economics and Logistics, 18(2): 192-210.
150. ZHANG, X., CHEN, M. Y. et al. (2019). *A Novel Hybrid Approach to Baltic Dry Index Forecasting Based on A Combined Dynamic Fluctuation Network and Artificial Intelligence Method.* Applied Mathematics and Computation, 361, 499-516.
151. ZHANG, J., ZENG, Q. et al. (2014) *Forecasting Spot Freight Rates Based on Forward Freight Agreement and Time Charter Contract.* Applied Economics, 46(29): 3639-3648.
152. ZHANG, J. and ZENG, Q. (2017). *Modelling the Volatility of The Tanker Freight Market Based on Improved Empirical Mode Decomposition.* Applied Economics, 49(17), 1655-1667.
153. ZHOU, Y., and ZHAO, P. (2016). *An Application of Genetic Programming in Nonlinear Combining Forecasting.* International Journal of Hybrid Information Technology, 9(6), 443-454.