Neural network applications of forecasting VLCC and Suezmax oil tanker freight rates in the main trade routes

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Abstract

Oil is one of the highest exported product in the world, accounting for 5,9% of the global value of all exported products. Forecasting the freight rates of oil tankers is of importance for many interest groups in the shipping market and oil market. The focus of this study is to understand how neural networks, specifically Levenberg-Marquardt, Bayesian Regularization and Scaled Conjugate Gradient algorithms perform for forecasting crude oil tanker freight rates, and if they provide better results than simpler methods. On the other hand, we focus to understand better what factors influence crude tanker freight rates. The study examines two vessel sizes VLCC and Suezmax, with three tanker routes, respectively the route from the Middle East to the U.S. (TD1), the route from the Middle East to Singapore (TD2) for VLCC and the route from the Black Sea to the Mediterranean (TD6) for Suezmax. The study takes into consideration nine variables which are: fleet development, bunker prices, new-building deliveries, crude oil demand, crude oil price, oil production, fleet development, fleet demolition, tanker order-book and new-building contracts collected for a period from May 2000 to December 2020. The variables are divided in three batches, and we see which of the variable groups performs best with each algorithm. We use MSE, R squared and RMSE as error measurement. We find that for short-term forecasting, for VLCC, the Scaled Conjugate Gradient algorithm performs best for batch two, by showing a smaller forecasting error. Regarding TD6 route by Suezmax, the best performing model is Bayesian Regularization. We compare the results with a simple naïve forecasting model, where for TD1 route it seems to perform good, but for the two other routes, neural networks outperform naïve forecasting.

Keywords: *Crude oil tanker, forecasting freight rates, neural networks, naïve forecasting, VLCC, Suezmax.*

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List of Abbreviations

ANN / NN : Artificial neural network

AGA : Adaptive genetic algorithm

ARIMA : Auto Regressive Integrated Moving Average

ARMA : Autoregressive moving average

BDTI : Baltic Dirty Tanker Index

BEKK : Baba, Engle, Kraft, and Kroner

DWT : Deadweight tonnage

GDP : Gross domestic product

LMA : Levenberg-Marquardt Algorithm

MATLAB : Matrix Laboratory

MBPD : Barrels per day

MSE : Mean squared error

NARX : Non-linear autoregressive model and exogenous input

OPEC : Organization of the petroleum exporting countries

RMSE : Root mean squared error

US : United States of America

SCG : Scaled Conjugate Gradient

ULCC : Ultra large crude carrier

VLCC : Very large crude carrier

WNN : Wavelet neural network

WS : Worldscale

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1. Introduction

1. Research background

Oil is an important liquid used in different sectors. It serves as a base for petrochemicals, road industry, marine bunkers, aviation, electricity generation, rails etc. Oil is one of the highest exported products in the world, accounting for 5,9% of the global value of all exported products. Global oil production was around 95,2 million barrels per day in 2019. (Sönnichsen, 2021). The consumption of oil from the United States in 2019 was 7.5 billion barrels, where 3.4 billion of them were used for gasoline fuel and 1.5 billion barrels were used for heating oil and diesel fuel (EIA, 2019). However, not every country produces crude oil, but they all depend on it.

Even though there is a rising in renewables, oil transportation remains one of the most important businesses nowadays and the whole world relies on it. Hence, oil tankers play a major role in the shipping industry. Therefore, forecasting their future freight rates is of importance for many interest groups in the oil market and shipping industry. The affected groups from oil freight rate volatilities are oil producers, oil traders, refineries, ship owners, charterers, banks that provide the loans, ports, brokers, investors and insurers. Demand and supply changes in crude oil affect its price, thus leading to changes in the whole economic system starting from the budget of families, corporates or GDPs of countries.

Freight rates forecasting helps to mitigate the risks that different actors in the maritime industry will face in the future. The freight rates are very uncertain, (Stopford, 2009) making it more difficult for maritime players to make decisions. But if this uncertainty is somewhat reduced by using reasonable and effective forecasting models, these actors would be able to make better decisions.

There are many studies and analysis about forecasting, not only in the tanker market but in other shipping markets too. Still, as the tanker market is continuously changing, updated analysis are necessary. Historically, decision-makers have based their decisions on gut feeling and intuition combined with market knowledge.

Some of the changes that have happen in the last decades are new technologies, growing ship`s sizes, widening of canals, deepening of ports, diverse chartering contracts and the shift in oil producing countries. All these factors have influenced the changes in the tanker market.

1.2. Problem description and research purpose

This study aims to contribute to the crude oil tanker market literature. The purpose of the study is to provide an improved prediction analysis of tanker freight rates with the use of neural networks. Improved forecasting will also provide more confidence to investors and bankers that create access for liquidity to ship owners and charterers.

Oil tanker markets expose big risks to different stakeholders due to their high cyclicality and volatility. For ship owners, for instance, it would be a risk to invest huge capital in the oil tanker market without predicting the potential in future. Past studies have shown that oil tanker markets are highly volatile and sensitive (Kavussanos, 2011; Tsouknidis, 2016; Molvik & Stafseng, 2018) due to different economic issues, geopolitical issues, market dynamics, utilization of the fleet, etc. (Lun et al., 2010; Stopford, 2009). The major oil price shocks have occurred during political events which also affected the disruption of the supply chain, such as Arab Oil Embargo, the Iran-Iraq War, the Persian Gulf War etc. (Hamilton, 2011). On the other hand, the freight rates in the last months during the year 2020, have been mostly driven by external forces such as the pandemic, which have consequently affected supply and demand (Lyridis et al, 2017; Michail and Melas, 2020). Crude oil contracting felt by 38% in 2020 compared to the year 2019. (Ovcina, 2020). The cargo carrying capacity of the oil tanker fleet grew by around 42% from 2010 to 2019, while the growth in demand was 6.3%. (Sand, 2020).

The global oil market is changing at a fast rate and some of the factors influencing this are new areas of oil producers and consumers (for example the US is depending less on oil import and more on producing in-house), changes of importers and exporters of crude oil, new technologies and digitalization in shipping, size of the ships, deepening of ports and widening of canals, etc. (EIA, 2020). The top oil-producing countries in 2019 with their respective share of global production were: United States (19%), Saudi Arabia (12%), Russia (11%), Canada (5%) and China (5%). (EIA, 2020). Besides being a leader in oil production nowadays, the U.S. is also the biggest consumer of it. Oil production means the extraction of oil from its reserves. The United States has become a leader in oil production since 2017, due to its new methods of drilling (Sönnichsen, 2021).

These issues have made the oil tanker market more complex and even more volatile, eventually affecting the business models and decisions making processes of maritime players and other interested third parties. Conventional market analysis is getting out of use, and more comprehensive, advanced and dynamic models are needed to better predict the future.

1.3. Research questions

Oil tankers have different sizes such as Handysize, Panamax, Aframax, Suezmax, Very large crude carrier and Ultra large crude carrier. In this study, we chose two ship sizes: VLCC and Suezmax and three routes in total, two for VLCC and one for Suezmax. We chose them because they mainly transport crude oil. The main routes taken into consideration are the ones which have the highest flow of transportation between markets. Each ship has different sizes and is employed in diverse routes. VLCC operates in four routes. Suezmax passes by Suez Canal and is more flexible than VLCC in terms of employment.

This study contributes to the existing literature by assessing the performance of advanced machine learning models in forecasting future freight rates of VLCC and Suezmax tankers. The results of this study might help stakeholders to make more sensible decisions by providing them with more accurate market changes predictions for the future. In this way, they can decide better on when is the right timing for chartering out the ships, what should be the charter rates, fleet size, etc.

The purpose of this study can be placed in the context of two research areas, which then will drive our research questions:

- **a.** What are the factors that drive volatility in the oil tanker market?
- **b.** Which models can provide improved forecasting of crude oil tanker market freight rates?

1.4. Thesis structure

The thesis is organized into seven chapters, including the introduction. The rest of the thesis is organized as follows: Chapter two reviews the previous literature relevant to this topic. Chapter three analyzes the factors that drive volatility in the oil tanker market, thus providing an answer to the first research question. Further, chapter four describes the selection and collection of data and covers the process of methods used to obtain results. In chapter five, the results are presented while in chapter six they are discussed. In chapter seven are drawn some final conclusions with an answer to the research question as well as some recommendations for further research. The thesis outline is presented in figure 1.

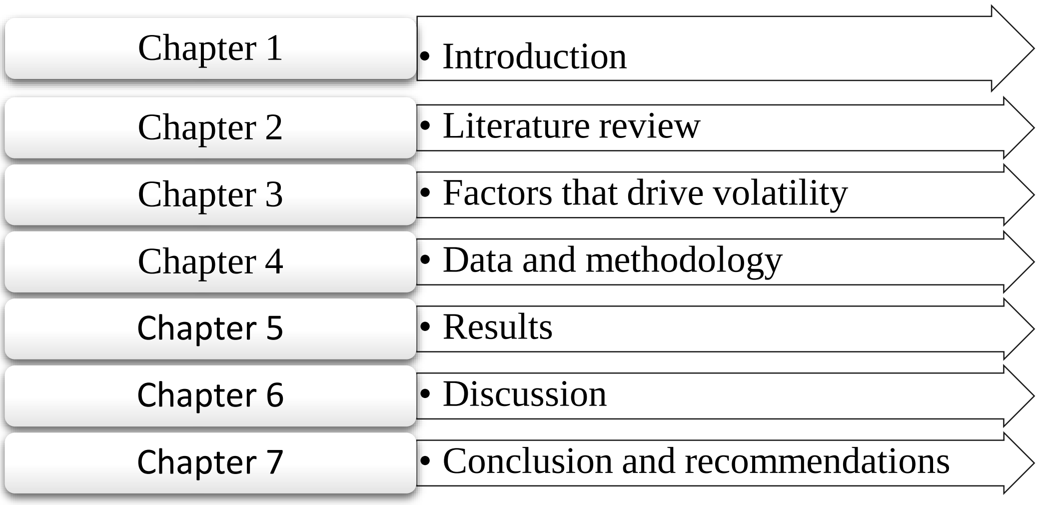


Figure 1: Structure of the study

2. Literature Review

2.1. The purpose of the literature review

For effective research, we should have an understanding of existing knowledge and ideas used by others, to learn as much from the scientific work they have done, and to improve our ability to critically evaluate research in this field. The goal of reviewing the literature in this study is to provide a context of the ideas that have been established earlier in the oil tanker market, determine the sources that will contribute to this topic, justify the choice of the research design, identify the main methodologies that have been used earlier and fill the gap in the existing literature. A literature review is therefore very valuable, to help us refine and hone the skills in analyzing valid data in the field of tanker freight rates forecasting.

2.2. Method used for finding and selecting literature

The steps followed in the study for establishing the literature review are as follow:

Step 1: *Identify relevant sources*

After having selected the topic of interest, presenting the research problem and questions, an identification of the relevant sources related to the topic was done. The sources of literature that have served for this study are secondary sources, mainly journal articles, books sections related to the topic, industry reports and internet sites. The author used the university library`s catalogue and databases such as Scopus, Web of Science and Science Direct to search for some keywords: forecasting, freight rates, oil tanker forecasting, and tanker freight rates, neural networks.

Step 2: Evaluate and select the most relevant sources

The group of sources identified, was further evaluated and narrowed down to the most relevant ones, related to our topic. The focus was to select not only highly relevant sources but also credible ones. For instance, the search for journal articles was refined to those “peer reviewed”.

Step 3: *Read, analyze and outline the literature review`s structure*

The sources were later grouped in themes and sub-themes of the topic. The structure of the body of the literature review is divided by themes. First, the concept and benefits of forecasting are given, then some research from previous studies is provided to see how other authors have used forecasting models and what findings they got in their studies.

Step 4: Write it down

After reading the relevant sources and outlining the structure, the literature review was written and narrowed down along the way.

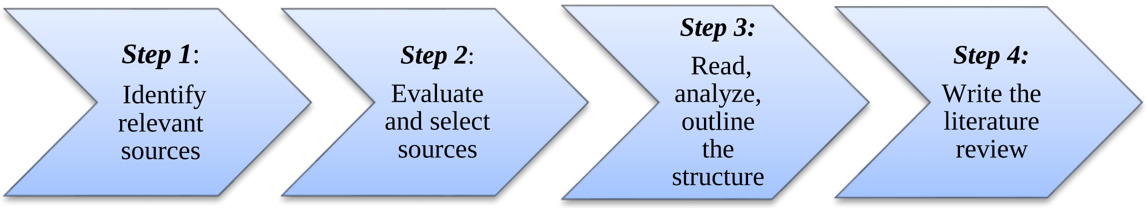


Figure 2: Steps followed to establish the literature review

In the following part, we will review previous literature regarding forecasting freight rates in general, the use of ARIMA model or naïve forecasting, and the use of more advanced neural networks models. There is a large number of empirical studies related to the tanker shipping industry, but our study is focused on freight rates.

2.3. Oil tankers

Tankers are ships used to transport liquid cargo in bulk. The tanker shipping market can be classified in terms of tanker size, cargo, region and shipment route. Crude oil tankers play a key role in the energy value chain. They transport crude oil from the points of production to refineries, where oil is further refined and then converted into different products. Sometimes they are used for oil storage after production.

Regarding vessel size tankers can be classified in: ultra large crude carriers (ULCC), very large crude carriers (VLCC), Suezmax, Aframax, medium-range (MR) and general purpose. VLCC has a storage capacity twice the capacity of Suezmax, around two million barrels of crude oil. Regarding cargo, tankers can be classified in oil tankers, chemical tankers and gas carriers. Cargoes include different types such as: crude oil, oil products, chemicals, vegetable oil, or liquefied gasses. Shipment routes can be segmented into coastal, inland and deep sea. Regarding regions, Asia is expected to be a leader in the tanker market due to rising demand for oil and chemical products, higher population and income.

Oil tankers are vessels of different sizes that transport oil and its products in bulk. They are low-speed vessels with a maximum speed of 15.5 knots. They are divided into two types: crude tankers and product tankers. Crude tankers transport unrefined oil from extraction points to refineries. Product tankers are smaller, and transport crude oil derivatives (refined products) from refineries to consumer markets.

VLCC carry up to two million barrels of crude oil and Suezmax carry up to one million barrels. Smaller tankers, such as Aframax are used to carry around 600.000 barrels, that`s why they are used to transport refined oil products, not crude oil.

Table 1: VLCC and Suezmax characteristics

Vessel	Dwt	Barrel capacity	Length	Breadth	Draught
VLCC	300,000	2,000,000	320	60	20
Suezmax	160,000	1,000,000	265	50	17

Source: Clarkson

If we look back in history, the size of oil tankers changed drastically in the mid-seventies, when oil trade was abundant, resulting in new 100,000 – 200,000 metric tons tankers constructed in Japan. In the late nineties, the oil prices went very high and the quantity of oil transportation fell, leading to the need of building VLCC and ULCC. (Chakraborty, 2021). The size of the ships may impose some constraints on the operation of the ships, regarding port requirements, storage capacity, economies of scale, ship facilities etc. For example, large ships may exploit economies of scale due to their big carrying capacity, but they often are unable to get backhaul cargo. Thus, investors in this market diversify their business by investing in different ship sizes.

Tanker size can be measured in cargo-carrying capacity, where the units are cubic meters or deadweight tons. Oil tanker sizes vary because of their beam and draft restrictions and are classified as:

- Handysize, Handymax, Coastal are the smaller category, with a size of around 10,000 to 50,000 dwt. Their small size gives them the advantage to access ports of different sizes and requirements.
- Panamax have a size of around 50,000 to 80,000 dwt. They are usually used to transport cargo for shorter distances, such as from Europe to the East part of the US.
- Aframax vessels have a size of 80,000 to 120,000 dwt. They are appropriate for short-to-medium-haul transport.

- Suezmax have a size of 120,000 to 200,000 dwt. They can reach Atlantic destinations via the Suez Canal, being the largest ships that can transit it. After Suez Canal upgrade, the maximum vessel draught is 21, 95.
- Very large crude carriers have a size of 200,000 to 320,000 dwt.
- Ultra large crude carriers have a size of 320,000 to 550,000 dwt.

VLCC and ULCC are called supertankers and they are used for long-haul transport. Their big size is an advantage for the economies of scale (lower transport cost/unit), but often is a disadvantage for entering different port sizes fully loaded. Until April 2020, there were 810 VLCC worldwide. (Sönnichsen, 2020)

2.4. General forecasting

Forecasting is the process we go through when we make a prediction or estimation for a future event. (Sanders, 2017). Forecasting involves the prediction of broader issues whether in our personal life or in business such as: the weather, politics, customer sales, product demand, resource shortage, making risk assessments, freight rates in transportation etc. The fact that most of the business decisions are based on forecasting, makes it a very important topic to study. Wrong decisions can bring very costly consequences in terms of wrong markets, lost sales and can lead the company to go out of business. According to Sanders (2017), forecasting is important for several reasons:

- Forecasting is the foundation of all decision making.

- Forecasting supports strategic decisions (long-term decisions) and tactical decisions (short-term decisions) of the companies in every industry.

- The accuracy of forecasting impacts costs and customer service.

According to Hyndman and Athanasopoulus (2018), the predictability of an event depends on how much data available we have for the forecasting, and how explicit are the factors that contribute to it. One of the challenges of forecasting is that it does not only need the right technology and forecasting methods depending on the field of the forecast, but it highly relies on human judgment. A more complete forecast will need a good statistical and sophisticated method and managerial judgment that comes from expertise and experience.

Forecasts are never perfect because the future is uncertain and forecasters will always have to face an amount of error, which is the difference between the forecasted values and the real values that will happen. Naturally, comes the question: why do we need a forecast when it is not accurate enough? It might not be perfect, but it still can be a good forecast, which can prevent large errors that could happen if businesses would not forecast at all. On the other hand, Sanders (2017) clarifies that forecasts are more accurate for short-term periods rather than long-term ones. When the time horizon increases, the relationship between data is more likely to change and make the forecasting less accurate.

2.5. Forecasting in the tanker market

Several empirical studies are focused on forecasting freight rates in the shipping industry. There are several models applied by researchers to forecast freight rates, among them: Autoregressive integrated moving average (ARIMA) model, vector auto-regression model (VAR), vector error correction model (VECM), artificial neural networks, etc. (Li & Parsons, 1997; Lyridis et al, 2004; Santos, 2013; Spreckelsen, 2013). Different forecasting freight rates studies are done in other shipping markets such as in the container market (Munim & Schramm, 2017; Luo et al., 2009), or in the dry bulk market (Franses & Veenstra 1996; Sahin et al., 2018).

Regarding the tanker market, Koopmans (1939) was one of the pioneers that has put effort into explaining the cyclical nature of shipping He made one of the earliest contributions in the econometric application of tanker freight rates. He analyzed the tanker freight rate determinants by observing how demand and supply intersect in their point of equilibrium when the world market is dominated by large oil companies. He observed and supported the idea that the tanker sector is perfectly competitive and that the demand is very inelastic. This means that there is low correlation between the demand and the freight rates. The basis for this finding is the fact that oil is always highly demanded by the market because it cannot be substituted. Shifting to alternative fuels requires large capital investments. Regarding supply, Koopmans (1939) differs between the case when all fleet is chartered and the case when ships are laid up. In the first scenario, the supply would be highly inelastic because there is little chance to increase the cargo capacity. Building a new ship takes more than two years. In the second scenario, the supply would be highly elastic, as there are a lot of unemployed ships, and freight rates are low.

That study was followed by numerous others, such as the one from Zannetos (1966), who also made significant contributions regarding the modelling of freight rates. The analysis was done between freight rates and variables such as: orders, lay-ups, deliveries, scrapping etc. He described that in the oil tanker market, freight rates have long troughs and short, sudden peaks. (Veenstra & De La Fosse, 2006). Zannetos found that the factor that affects the freight rates is the size of the ship, and they are negatively related.

As stated earlier in the thesis, there are some studies that show that oil tanker freight rates are highly volatile. Kavussanos (1996) explores volatility as an indicator of risk for second-hand ships in the tanker market. He used an autoregressive conditionally heteroscedastic model (ARCH) to compare time-varying risks between vessels that have different sizes. In the study, monthly price returns of smaller vessels were found to be generally less volatile than those of larger vessels. In addition, the VLCC and Suezmax tankers observed a downward trend in the risks, indicating that the overall risks in the tanker industry have declined since 1980. Later, Glen and Martin (1998), supported the widely held view that the degree of risk involved in bigger size tankers (for instance VLCC) is higher than the risk in smaller size vessels. In addition, using the GARCH model, their study provided support for the theory that employing ships in the spot market is riskier than operating them in the time charter market.

In another study by Zhang et al (2016), were modelled the volatility spillovers between the freight rates of VLCC, Suezmax and Aframax by using the BEKK-Multivariate generalized autoregressive conditionally heteroscedastic model (GARCH model). Similarly, Gavriliidis et al. (2018), used the GARCH model to measure the volatility forecast by including the oil price shocks as an exogenous variable. They concluded that aggregate oil demand shocks and precautionary oil-specific demand shocks improve the accuracy of the volatility forecast of tanker freight rates. Lyridis et al. (2017) used the FORESIM simulation technique to model the tanker market future risks. Their study indicated that the key external variable that affects the tanker market is OPEC oil production level, and FORESIM seemed to represent a promising tool in simulating freight rate time series.

Another model called BEKK-GARCH was used by Dai et al. (2020) to analyze the Baltic dirty tanker index and Brent oil prices from January 2007 to November 2015. They focused mainly on the volatility transmission mechanisms between the tanker shipping market and the international crude oil market. This period covered volatile prices caused by oil price shocks and the financial crisis of 2008-2009. The study indicates that in a long-term period, the volatility is transmitted from the crude oil market to the tanker market and not vice-versa. On the other hand, Adland and Cullinane (2004) studied the dynamics of the freight rates in the oil tanker market, by using a non-parametric Markov diffusion model. In their study, they provide evidence that the dynamics of spot freight rates can be described by a non-linear stochastic model.

Other studies have proven that using freight forward agreements (FFA), helps in improving the forecasting performance of spot freight rates. (Zhang, Zao & Zeng, 2016; Batchelor, Alizadeh & Visvikis, 2007). Zhang et al. (2014), used a VECM model to analyze the relationship between spot rates and FFA, and between spot rates and 6-months' time charter contract in capesize vessels. They found that there is co-integration between both relationships, and the forecasting gets even better if there is integration between FFA and TC.

The application of neural networks in the freight market for oil tankers is used by many researchers, but still deserves more attention as an analytical tool. Li and Parsons (1997), who were among the first to perform artificial neural networks in forecasting tanker freight rates, concluded in their study that neural network models outperformed ARIMA time series models, especially for longer-term forecasting.

Lyridis, Mytrou and Mylonas (2004) researched in forecasting VLCC spot freight rates. The NN they implemented in their study were multilayer perceptron networks. They analyzed a period from October 1979 to December 2002 and found that artificial neural networks outperformed naïve forecasting model in three to twelve months ahead of forecasting. However, for a 1-month forecast, the error is comparable to that of the naïve method. Later, Eslami et al. (2017), used a hybrid approach, by combining neural networks with an adaptive genetic algorithm to forecast VLCC freight rates, in an attempt to get better results than the study of Lyridis, Mytrou and Mylonas (2004). They used three parsimonious variables: crude oil price, fleet productivity and bunker prices, and found that their approach was superior to that of previous studies, with a lower RMSE of 11.2 WS. Fan et al (2012) used the wavelet neural network (WNN) model to forecast BDTI. Their study identified that traditional models like ARIMA, are weak in forecasting longer periods of such complex shipping indexes. WNN can be more effective in forecasting non-stationary and non-linear shipping indexes.

Another effort of NNs application in VLCC tankers was done by Santos, Junkes and Pires (2013). The authors were focused on period charter rates rather than spot rates. They used monthly charter rates data of VLCC tankers for 1 and 3-year time charter parties. They considered two alternative specifications such as: NNs multilayer perceptron (NN-MLP) and radial basis function (NN-RBF). The results of their study indicated an overall satisfactory performance of NNs, especially of NN-RBF, which outperformed ARIMA model that was used as an alternative model for benchmarking purposes. Their study concluded that neural network models, indeed, provide a better result for period tanker rates for VLCC tankers. A similar forecasting of spot and forward freight rates in the tanker shipping market with linear and non-linear forecasting models was done by Spreckelsen, Breitner and Mettenheim (2013). Their findings also supported those of previous research, but in contrast with the long-term theory, they found that non-linear methods such as neural networks perform well in short-term forecasting.

A Markov regime-switching regression model was used by Stafseng and Molvik (2018), with two states, a normal state and a volatile state, to predict one month the time charter equivalent of six tanker routes. They found that parsimonious models outperform variable-rich models; regime models on never-before-seen-data yield promising results; route-specific regime models improve the forecasts as opposed to the generic factor-driven models.

Another use of neural networks is seen in forecasting dirty tanker market earnings, by Jung (2019). He analyzes different variables from 2000 to 2016 for three tanker sizes: Aframax, Suezmax and VLCC. The algorithms used were Levenberg-Marquardt and Bayesian, and the forecast was done for 3, 6, 9, 12 and 15 months ahead. He found that the Bayesian algorithm performed better. Additionally, for 3, and 9 months-ahead forecasting, the neural networks with a lower number of hidden layers, performed better, whereas for the 12 and 15 months-ahead forecasting, a greater number of hidden layers provided better performance.

To conclude, we see that the majority of previous studies show that the more complex statistical methods such as artificial neural networks, provide a better forecasting performance when compared to ARIMA or naïve forecasting models. In the table below are summarized some of the main findings of previous forecasting studies.

Table 2: Summary of some of the main literature review related to forecasting tanker freight rates.

No.	Article Title and publication year	Author(s)	Data type	Route	Forecast methods	Best performing method	Implication for policy/literature
1.	Forecasting tanker freight rates using neural networks (1997)	Li & Parsons	Monthly data from January 1980 to October 1993	The route across the Mediterranean	NN and ARMA model	NN model	Neural network models outperformed ARMA time series models, especially for longer-term forecasting.
2.	Forecasting tanker market using artificial neural networks (2004)	Lyridis, Mitrou, Mylonas & Zachariou dakis	VLCC spot freight rates (WS) for 1, 3, 6, 9 and 12 months ahead. 1979-2002	Middle East Gulf – Roterdam	ANN used in the paper are multilayer percepton network	NN model	NN outperformed naïve forecasting model in 3-12 months ahead forecasting. For 1-month forecast, the error is comparable to that of naïve method.
3.	Forecasting Baltic Dirty Tanker Index by applying wavelet neural networks. (2012)	Fan, Gordon, Ji & Rickard.	Daily BTDI data from 1998 - 2012	-	WNN and ARIMA as a benchmark model	WNN model	No significant difference between two models, in short term. WNN have better forecasting accuracy than traditional techniques, for long-terms.

4.	Forecasting period charter rates of VLCC tankers through neural networks: A comparison of alternative approaches (2013)	Santos, Junkes & Pires	Monthly observations from 1994 to 2010 of VLCC time charters parties of 1 and 3 years.	Arabian Gulf - Japan	1) NN with two alternative specifications such as: NNs multilayer perceptron (NN-MLP) and radial basis function (NN-RBF) & ARIMA	NNs, especially NN-RBF	NN models, provide a better result for period tanker rates for VLCC tankers. Overall satisfactory performance of NNs, especially of NN-RBF, which outperformed ARIMA.
5.	Predicting tanker freight rates using parsimonious variables and a hybrid artificial neural network with an adaptive genetic algorithm (2017)	Eslami, Jung, Lee & Tjolleng	VLCC monthly data from 1983-2003	Ras Tanura-Rotterdam	Prediction model based on ANN and an adaptive genetic algorithm(AGA)	ANN + AGA results outperform regression approach	RMSE = 11.2 WS, slightly superior to previous studies.
6.	Forecasting time charter equivalent oil tanker freight rates (2018)	Stafseng & Molvik	Monthly data. 6 dependent variables and 163 independent variables. 1-month ahead	6 tanker routes: TD1, TD3, TD7, TD12, TC1, TC2	Markov regime switching regression model with two states, a normal state and a volatile state, accounting for seasonality, lag and global factors.	Parsimonious models outperform variable-rich models.	Regime models on never-before-seen-data yield promising results. Route-specific regime models improve the forecasts as opposed to the generic factor-driven models.

3. Tanker freight market and factors that affect them

To understand what the factors that affect the tanker market are, we need to see how its demand and supply interact. Before that, let`s take a look at the shipping cycles, freight market and its rate mechanisms.

3.1. Freight rate mechanism and shipping cycles

The freight rate mechanisms link supply-demand theory with shipping cycles. The factors that affect the shipping demand include the world economy, average haul, transport costs, while the factors that affect the shipping supply are operational efficiency and fleet size (Lun et al. 2010). In the crude market, the supply function shows the quantity of crude oil sea transport that the carriers would offer for each level of freight rate. The demand function shows the quantity of crude oil transport that shippers would purchase for each level of freight rate (Lun et al. 2010). Shippers and carriers negotiate together to accept a mutual freight rate, which causes supply and demand to intersect at the equilibrium point.

The fluctuations of these freight rates, create shipping cycles which can be seasonal, short and long cycles or secular trends (Stopford, 2009). Seasonal cycles occur within one year and are caused by seasonal patterns in demand and supply of the products, which in turn influences freight rates. Short cycles occur within three to twelve years, and consist of four stages (Stopford, 2009):

Stage 1: Trough. In this stage there is an excess of supply and low demand. Freight rates are low, they decrease in operating costs, and old ships prices fall to scrap prices.

Stage 2: Recovery. Freight rates start to increase above operating costs, as supply and demand move towards the equilibrium.

Stage 3: Peak. Freight rates rise 2-3 times more than operating costs, 5-years old ships have the same price as new-building ships, and there are heavy new-building orders.

Stage 4: Collapse. Freight rates fall, as supply starts to exceed demand, and the least attractive vessels wait for cargo.

Long cycles are also called trends because they occur for long periods of time, up to 50 years, and are usually driven by economic, technical or regional changes (Stopford, 2009).

In the shipping cycles, demand and supply continually interact with each other to determine freight rates. When there is a shortage of ships and high freight rates, this stimulates the new ordering of ships, which will eventually lead to more supply of ships (Lun et al., 2010).

3.2. Freight market

In shipping there are four markets (Stopford, 2009): new-building market, sales and purchase market, freight market and demolition market. The main stakeholders in the shipping markets are shipowners, charterers, brokers, and shipyards. Shipowners own a fleet of ships and operate them in different shipping segments. Charterers hire the ships, and they want the ships to meet their needs, in terms of contract length, cargo carrying capacity, fuel consumption etc. Thus, freight rates and contract terms affect the cash flow of ship owners and transportation costs of charterers.

Based on the factors mentioned above, there are four types of contracts which are known as charter parties in the freight market, between shipowners and charterers. These contracts differ based on what responsibilities and costs covers each of the parties in the contract. There are two types of costs: operational costs are related to running costs of the ship, such as insurance costs, stores, spares, lubrication oil, maintenance costs etc, while voyage costs are associated to the ship employment such as bunker, port charges, taxes, fees etc.

3.3. Variables that affect tanker freight rates

As in every commodity market, also the tanker market is affected by the interaction between supply and demand for tanker shipping services. The changes in supply and demand create volatility in the crude tanker freight rates.

3.3.1. Demand for oil tankers

Martin Stopford in his book "Maritime Economics" has provided the fundamentals of shipping theories. According to Stopford (2009), there are five variables that affect the shipping demand:

a) The world economy, b) seaborne commodity trades, c) average haul, d) random shocks, e) transport costs.

The world economy effect can be seen in two aspects, business cycles and trade development cycles (regional cycles). Business cycles create the foundation for freight cycles, as the fluctuations in the economic growth, directly affect the seaborne trade. While business cycles determine short-term trends, regional cycles determine medium-to-long term trends in the sea trade. These cycles then determine the sea trade volume of commodities, such as crude oil products. The commodities in turn, are affected by the average haul or distance of the crude oil shipped in different routes, random shocks and transportation costs (Stopford, 2009). Transportation costs affect the demand for oil tankers, because the lower the costs, the higher the demand for transporting crude oil. Lower bunker prices and efficient utilization of the ships help reduce transportation costs.

A typical example of how regional cycles affected crude oil demand was in 1960, when oil was cheap and Western Europe and Japan started to import oil as their primary energy source. But in 1970, the trend reversed, as the oil prices went up, causing the demand to stagnate and decline (Stopford, 2009).

The main factor that drives volatility in the tanker demand is the demand for oil, which in turn is influenced by the whole world economy and consumption of energy products. In general, factors that influence oil tanker demand are: the growth of the world economy, oil shocks, war, oil reserves, oil price, seasonality, climate conditions, political decisions (OPEC policies), and new reserves (Eslami et al, 2016).

When the economy is booming and performing well, more oil will be needed to complete the needs of various industries, thus if the demand rises and supply cannot rise to match it, oil prices will go up. Similar patterns will follow in the periods of recession, if the global demand for oil drops, supply will be higher than demand and prices will go down. In the past years, the U.S. has been the biggest driver of demand while OPEC the biggest driver of supply. In the latest years though, alternative resources have arisen, modern drilling technologies have increased the supply in different areas including US and China has become a major consumer.

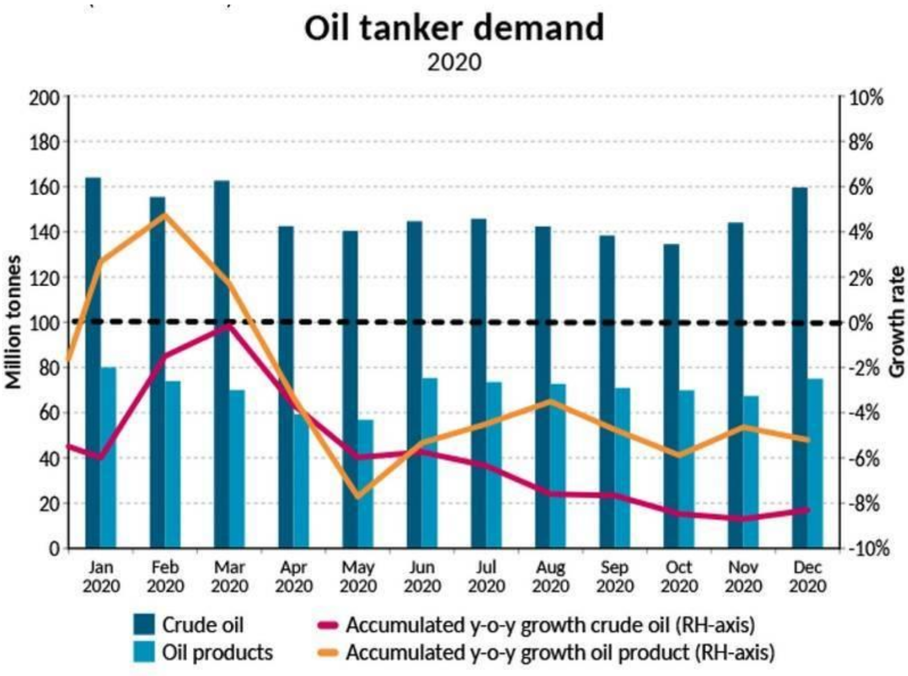


Figure 3: Oil tanker demand in 2020. Source: BIMCO, Tradeviews.

Global oil demand fell by 8.9 % in 2020, from 101.2m barrels per day to 92.2m bpd. (EIA, 2021). Demand for crude oil tanker shipping fell by 8.3%.

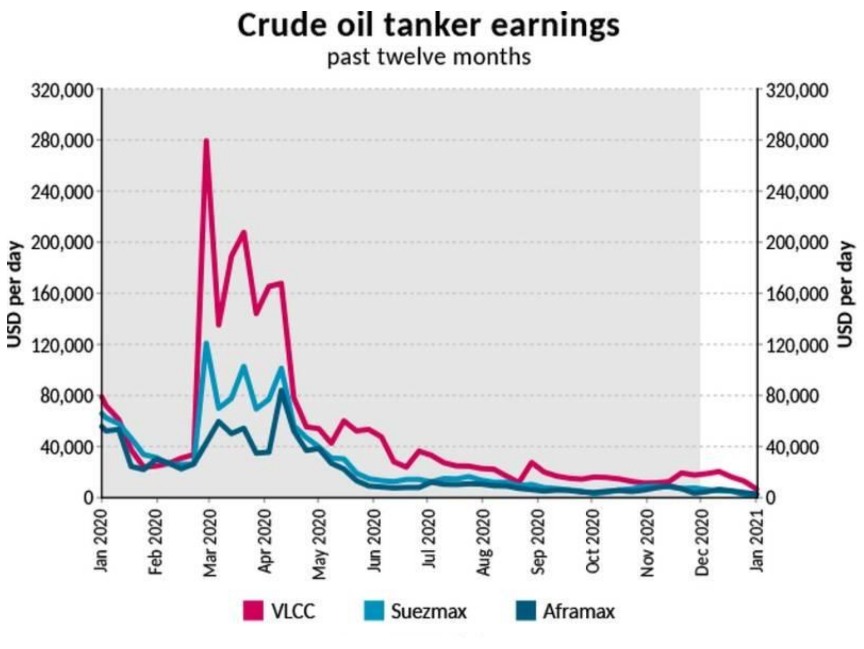


Figure 4: Crude oil tanker earnings in 2020. Source: BIMCO, Clarkson.

Oil tanker market earnings have followed a similar pattern to the curve of crude oil demand, where there was a peak in March 2020, due to low oil prices and increased imports. After all the delays in the supply chain, the demand fell and since then the crude oil tanker earnings have been depressed too.

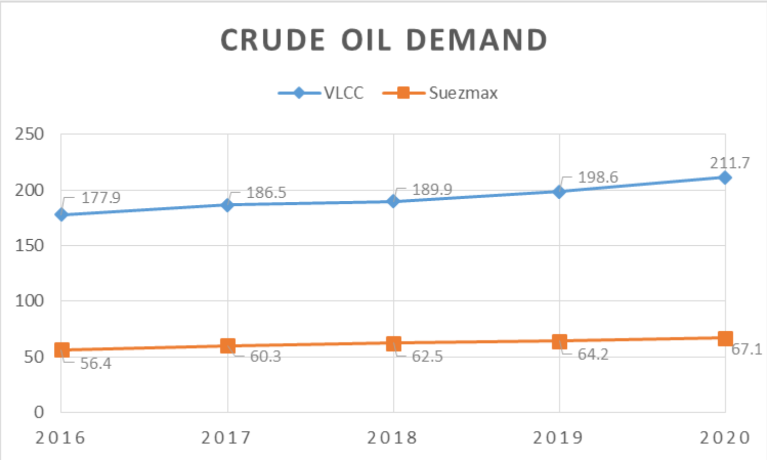


Figure 5: Crude oil demand in million dwt from 2016 to 2018. Adapted by the author. Source: Clarkson Research.

3.3.2. Supply for oil tankers

There are five other variables that affect the shipping supply (Stopford, 2009):

a) World fleet, b) fleet productivity, c) shipbuilding production, d) scrapping and losses, e) freight revenue.

The fleet of tankers offers a limited transport stock capacity, and it can be increased with new-buildings and reduced with tanker scrapping. Speed and logistical efficiency with which tankers operate affects also the amount of cargo that the fleet transports. This is known as fleet productivity. Tanker`s supply depends on tankers fleet size, its productivity, tankers deliveries, new-building price, order-books, scrapping price, new-building capacity, repair costs and the tonnage available for trading. Also, relocation of supply sources has affected the oil supply. For instance, in 1960, the Middle East was the main source of crude oil, while in 1970, new sources were found in the North Sea and Alaska. On the other hand, some of the major crude supply disruptions in the last years have deeply affected crude oil prices, and as a result crude tanker market supply and demand, as shown in table 3.

Table 3: Major crude supply disruptions.

Year	Major disruption
2020	Oil price war between Russia and Saudi Arabia known as OPEC crash
2019	Saudi Attacks
2014	Brent crude oil fell by 44%
1980	Iran-Iraq war, oil prices began a steady decline over the next 20 years
1979	Second shock, the oil price went over to 39$ / barrel, which caused fuel shortages
1973	First oil shock, as a result of OPEC embargo towards nations supporting Israel, the oil price raised to 300%

Source: EIA

Similar to tanker demand, tanker supply is directly influenced by oil supply. Oil supply is mostly affected by production interruptions or expansion, caused by OPEC and non-OPEC countries and geopolitical influences which cause supply shocks. The oil glut, for instance, happened in 2014-2015, and was caused as a result of an oversupply of US and Canadian shale oil, slowing economic growth in China and geopolitical competition between oil-producing countries. Crude oil production disruption affects the crude oil price. These price shocks, in turn, affect the transportation costs in the crude oil tankers, because bunker prices are correlated with crude oil prices (Gavriilidis et al, 2018).

The tanker market stayed strong at the start of the pandemic, and ended up in stagnation later during the year 2020 when other markets started to recover (Sand, 2021). The major oil producers decided to stop the high production, which led to lower crude oil demands and lower earnings. By the end of 2020, the number of Suezmaxes employed were low, while VLCC kept a more constant level of employment, still below the peak level. In April 20th, the price of oil became negative, as never seen before. Covid-19 travel restrictions dropped the demand for crude oil. On the other hand, there was what is known as the OPEC crash, where Russia and Saudi Arabia both increased oil production (Wikipedia, 2021). These factors caused a big gap between oil supply and demand, because demand was very low and supply high. Looking at these disruptions and other events that have drastically affected the tanker market, can be said that political instability and geo-political issues are a major factor that influences the supply for tanker demands, and as a consequence the freight rates too.

To summarize both supply and demand drivers, the main factors that drive volatility to crude tanker freight rates are found to be: world economy, oil demand and supply, oil prices, oil shocks, climate conditions, war and crisis, seasonality, new-building orders, fleet productivity, repair costs, new-building capacity, vessel tonnage availability, shipbuilding deliveries, geo-political decisions, new reserves and scrapping prices (Koopmans 1939, Zannetos, 1996; Stopford, 2009; Eslami et al 2016).

4. Methodology

4.1. Research design

Research design acts as a roadmap that helps the researcher to answer questions such as "what should we observe", "how will the data be collected", helps him to find solutions and guides him during each different phase of the analysis. (Nachmias, 2018, p. 88). It is a logical plan that links the initial questions of the study to the data and conclusions. There are various research design types such as: experimental, cross-sectional, exploratory, historical, descriptive, causal etc. This research has a historical design type because the authors have collected and synthesized data from the past to create evidence to the research question/and hypothesis. The data used are historical data, officially recorded from a reliable institution, thus making them authentic and valid. This approach suits best for trend analysis. A quantitative approach is chosen because it is more suitable for this kind of research, to collect numerical data and assess them in the software.

On the other hand, the study has a deductive research approach, because it aims to confirm a theory by observing the data. A deductive reasoning is a top-down approach. (Gabriel, 2013).

4.2. Data collection

The data in this paper are quantitative data. A quantitative research contains numeric data, which are analyzed with statistical methods. The purpose of using quantitative research is to discover a phenomenon that we assume exists, and to try to explain it by collecting data from the real world.

As mentioned earlier, the type of the research is secondary, because the data are collected through Clarkson Institute. There are two kinds of variables used in the paper, dependent and independent. The dependent variable is the one we want to understand and predict. The independent variables affect and serve as explanatory variables for the dependent variable. The dependent variables in the study are the freight rates that will be forecasted, which are represented by the Baltic Dirty Tanker Index (BDTI) for the three routes. Freight rates are measured based on the international freight index, worldscale. It represents a system for estimating tanker freight rates, in US dollars per tonne. Agreed freight rates are reflected in the worldscale index. Baltic Dirty Tanker Index is an assessment index in the tanker market. It indicates the cost of unrefined oil, on an average cost of 17 routes. There will be nine independent variables taken into consideration, as shown in table 4. In chapter three, we discussed about some main factors that influence crude tanker market. As we saw, crude oil prices, crude oil demand and its production, new-building deliveries and order book, fleet development, bunker prices were factors that affect oil tanker supply and demand. We add also new-building contracts for a thorough view of the factors.

Table 4: Independent variables of the study

Independent variables	**Description**
Bunker Prices	Monthly bunker prices for different destinations that affect the study, such as Los Angeles, Japan, Houston, Fujairah, Gibraltar etc.
New Building Deliveries	New-building deliveries for VLCC and Suezmax in deadweight tonnage.
Crude Oil Demand	Crude oil imports and exports for the US, EU, Mediterranean and Red Sea, expressed in barrels per day.
Crude Oil Price	Two crude oil prices applied are Brent crude oil price and Arab crude oil price.
Oil Production	This variable includes North America, Middle East, OPEC and global oil production in barrels per day (mbpd).
Fleet Development	Fleet development for VLCC and Suezmax in deadweight tonnage.
Fleet Demolition	Fleet demolition for VLCC and Suezmax in deadweight tonnage.
Tankers Order Book	VLCC and Suezmax orderbook in deadweight tonnage.
New-Building Contracts	VLCC and Suezmax contracts in deadweight tonnage.

The data sets were obtained from Clarkson Research Services for two tanker sizes, VLCC and Suezmax, for a total of three main routes. The data are collected monthly for a period from May 2000 to December 2020. In total, there are 248 observations of data for each variable. Some descriptive statistics for the freight rate indexes for the three routes are presented in table 5.

Table 5: Descriptive statistics

Variable	N	Mean	SD	Min	Max
BDTI- TD1	248	53.6	34.6	15.2	215.6
BDTI- TD2	248	76.2	44.3	26.9	318.3
BDTI- TD6	248	114.5	54.1	44.2	362.4

As stated previously, the purpose of this study is to find an optimal forecasting model that performs better and gives the smallest percentage error, by using neural networks. We train the models by using Matrix Laboratory (MatLab) software. MatLab is a tool for programming that allows analysis of systems, implementation of algorithms, plotting of functions and data that includes deep learning and machine learning. (Matlab).

The study performs neural networks such as Levenberg-Marquardt, Bayesian algorithm, and Scaled Conjugate Gradient algorithm.

4.2.1. Data batches

To see which group of independent variables are mostly correlated to tanker freight rates, and which group performs best, we have divided the variables in three batches, by adding more variables in each following batch, as in figure 4:

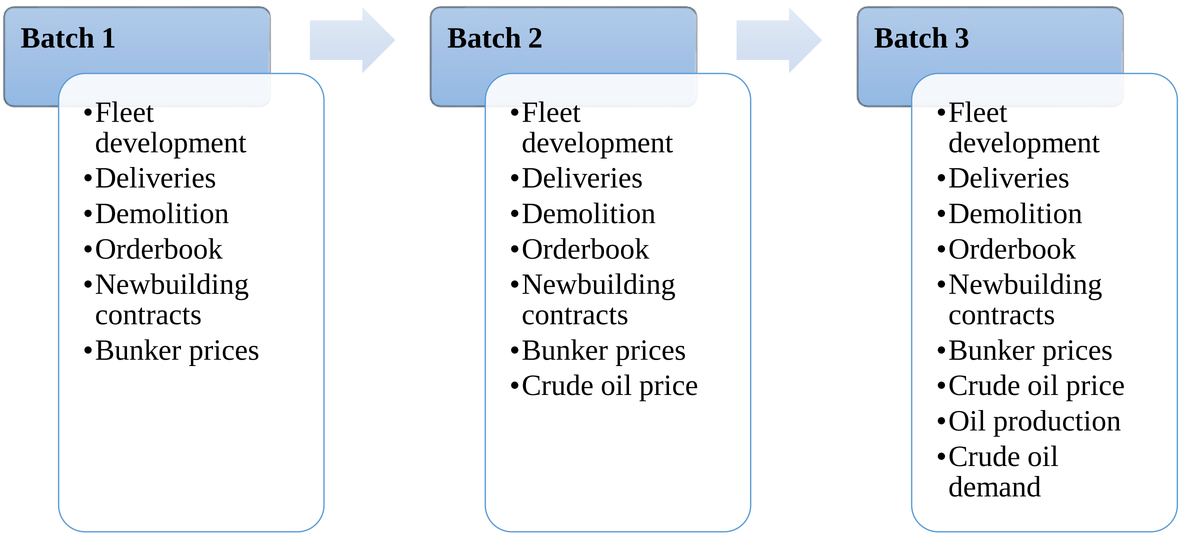


Figure 6: Data Batches

4.3. Routes

The market level for the routes is described by the Baltic dirty tanker index (BDTI). Saudi Arabia is the third largest oil producing and oil exporting country in the world, after the US and Russia. Thus, two of the routes of VLCC are from the Middle East Gulf to the US, and Singapore.

The two routes chosen for VLCC vessels are:

TD1 (280,000 tonnes) is the route from the Middle East Gulf to the U.S. Gulf. Ras Tanura, located in the Middle East Gulf, is the main terminal of Saudi Arabia. Crude oil is transported to the Louisiana offshore oil port (LOOP). Laydays/cancelling 20/30 days from index date.

TD2 (270,000 tonnes) is the route from Ras Tanura to Singapore. This is one of the world`s most traded tanker routes. Laydays/cancelling 20/30 days from index date.

The route chosen for Suezmax is:

TD6 (135,000 tonnes) is the route from Novorossiysk in the Black Sea to Augusta in the Mediterranean. Laydays/cancelling 10/15 days from index date. The table below presents the chosen routes by VLCC and Suezmax (Baltic Dirty Tanker Index, 2021).

Table 6: VLCC and Suezmax chosen routes

Routes	***Vessel size (dwt)***	***Route description***	***Vessel***	***Distance (nautical miles)***
TD1	280,000	Middle East Gulf to U.S. Gulf	VLCC	10,890
TD2	260,000	Middle East Gulf to Singapore	VLCC	4,266
TD6	135,000	Black Sea to Mediterranean	Suezmax	1,626

(A) TD1 route, VLCC

(B) TD2 route, VLCC

(C) TD6 route, Suezmax

Figure 7: Oil tanker routes: TD1, TD2 and TD6

4.4. Time series forecasting

A time series is a group of data points listed in time order that is measured in even-spaced intervals. It can be used to track any variable that changes over time. (Hayes, 2021). Time series forecasting uses historical values to predict future values. A time series can be composed of three factors: trend, seasonality and cyclicality. The trend is a long-term movement which might be the effect of general economic changes, inflation, population growth etc. Seasonality is related to increase and decrease of values due to calendar holidays and other calendar effects. Cyclicality is long-term and might have a duration of many years, such as business cycles.

4.5. Forecasting models

Forecasting methods vary from simple one to more complex methods. The simplest method is naïve forecasting, by using the recent observation as a forecast. Whereas a complex method is using neural networks, complex econometric systems etc. In this study we use naïve forecasting as a simple method and neural networks as an advanced method.

4.6. Naïve forecasting

Naïve forecasting is a very simple method and the most basic to predict future values. With naïve forecasting, previous periods are used to forecast next periods.

$$Ft + k = Yt \qquad (1)$$

Even though these are simple methods, they are useful and offer some accuracy levels. Naïve forecasting is also mostly used as a benchmark, to compare more complicated models with a baseline. (Shmueli & Lichtendal, 2016, p.50). From the studies mentioned previously in the literature review, Lyridis et al (2004) have used naïve forecasting to compare it with artificial neural networks.

4.7. Neural networks and NN architecture

An artificial neural network is a computing system that consists of many interconnected neurons (hidden units), that simulates the biological brain principles, the way human brain functions and analyzes (Alexandridis & Zapranis, 2014, p.17). It is a component of artificial intelligence and is used to solve problems that would be difficult to be solved by humans. The weights of interconnected neurons determine the strength of the signal that passes through them. Neural nets capture complex relationships between response and predictors. (Shmueli & Lichtendal, 2016, p.189). Some of the first studies that included neural networks in forecasting freight rates were by Li & Parsons (1997), Lyridis et al (2004). Later, more studies followed such as those of Santos, Junkes & Pires (2013), Eslami et al. (2017), Munim & Schramm (2020) and so on.

A neural network consists of multiple layers, and the output of one layer performs as input of the other layer. It includes three layers: the input layer, hidden layer and output layer. The identification of NN architecture involves these steps: (1) Selection of the number of hidden layers, (2) selection of the tapped delay lines, (3) selection of the training algorithm, (4) network validation and testing.

To avoid overfitting of the data, we use data partitioning, where the time series is divided in three parts. Overfitting happens when the model does not fit only to the component of the data but also to the noise. (Shmueli & Lichtendal, 2016, p.45). In this study the data for training NN models are divided into: training, validation and test data. 80% of the data will be used for the training, 10% as validation of the network and 10% will be used as testing for the generalization of the network. There are 248 sets of data in total, and 198 are used for training, 25 for validation and 25 for testing. The training set is used for building the data we are examining and learning and serves to identify the weights. The validation set serves to select the number of hidden nodes and assess model`s performances, while the test data serve to assess the performance of the chosen model.

There are ten hidden neurons and two delayed. We use the NARX network which stands for non-linear autoregressive with external (exogenous) input. It is used to predict future values of a time series y(t) from past values of that time series and past values of another time series x(t). Its equation is as follows (Beale, Hagan & Demuth, 2010, p. 68):

$$Y\ (t) = \ f\ \big(y\ (t-1), \dots .\ y\ (t-d), x\ (t-1), \dots .\ x\ (t-d)\big) \qquad (2)$$

The standard NARX network is a two-layer feed-forward network, with a nonlinear function in the hidden layer and a linear transfer function in the output layer. This network uses tapped delay lines to store previous values of the x (t) and y (t) sequences. (Beale, Hagan & Demuth, 2010).

4.7.1. Levenberg-Marquardt

The Levenberg–Marquardt or differently called LMA was developed in 1960`s and is used to solve nonlinear least squares problems. It combines two other methods: the Gradient Descent and the Gauss-Newton. The latter are iterative algorithms, which means they use a series of calculations to find a solution.

$$F\ (x) = \frac{1}{2} \sum_{i=1}^{m} [f_i\ (x)]^2. \qquad (3)$$

Gradient Descent was first suggested by Cauchy in 1847. It is an iterative optimization algorithm that operates by minimizing a specific function to a local minimum. (Gavin, 2020). With this algorithm, the solution updates by choosing values that make the function value smaller. The sum of the squared errors is reduced by moving toward the direction of lower value. The higher the gradient, the steeper the slope, meaning that the model can learn faster. When the slope is zero, the model does not learn.

Gauss-Newton is used for least squares problems. It can minimize the sum of squared errors. At each iteration, the Levenberg–Marquardt algorithm chooses either the Gradient Descent or Gauss-Newton and updates the solution. It usually uses more Gradient Descent when the parameters are far from optimal values and it uses Gauss-Newton when the parameters are close to optimal values. (Gavin, 2020).

4.7.2. Bayesian Regularization

Different researchers have used Bayesian Regularization, not only in the shipping industry but also in other areas. Some studies using Bayesian Regularization are done by Yan et al (2016), Shi et al (2019) or Burden & Winkler (2008). Bayesian regularization is a mathematical process that converts a nonlinear regression into a statistical problem in the manner of a ridge regression. (Burden & Winkler, 2008). Ridge regression is used to create a parsimonious model, when the data has multicollinearity, meaning when the predictor variables have correlations with each other.

4.7.3. Scaled Conjugate Gradient

The scaled conjugate gradient algorithm (SCG), is based on conjugate direction. A conjugate gradient is a mathematical method used to optimize linear and non-linear systems and it works as an iterative algorithm. Different from other conjugate gradient algorithms, SCG does not perform a line search at each iteration. This algorithm was created to reduce time-consuming line search. (Babani et al, 2016).

5. Results

This section will report the relevant results for all the four routes chosen, without discussing them and comparing with the established theory. First, we discuss the forecast accuracy measures that will be used to measure the accuracy of the results obtained, then we will present the respective results for each route.

5.1. Forecasting accuracy measures

To assess the predictive performance, we consider these measures of forecast accuracy: mean squared error (MSE), coefficient of determination ($R^{2)}$ and root mean squared error (RMSE).

MSE measures the average squared errors, thus the difference between actual and estimated values. Its formula is as follows:

$$MSE = \left(\frac{1}{n}\right) * \Sigma \,(actual - forecast)2 \qquad (4)$$

Where:

Σ – The sum
n – Sample size
Actual – the actual data value
Forecast – the forecasted data value

R^2 is used to explain how differences in one variable can be explained by a difference in another variable. It represents a value between zero and one, and is described in percentage, where a value of 0.9 means that 90% of the variation in Y can be explained by X-variables.

RMSE is the standard deviation of the prediction errors, and it tells us how concentrated the residuals are around the line of best fit. Its formula is:

$$RMSE = \sqrt{MSE} \qquad (5)$$

In figure 3 is presented the neural network with 10 hidden layers and two numbers of delays.

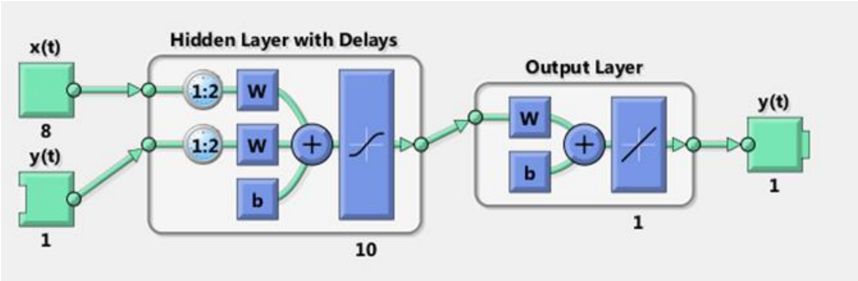


Figure 8: Neural Network with 10 hidden layers and 2 number of delays

5.2. Neural network results

5.2.1. TD1 route: Middle East Gulf to US Gulf

After training the three variable batches of TD1 route, we found out that batch one (Bayesian) and batch two (S.C.G.) provide similar results. But to create a fair comparison between all three routes, we will keep the same batch of variables, so we keep batch two. As we can see from table 1, the model that performs better for batch two is Scaled Conjugate Gradient, with the values of MSE, R^2 and RMSE, respectively 595.02, 88.4% and 24.3.

Table 7: Results for TD1 route, three batches and three algorithms.

	Batch 1			Batch 2			Batch 3		
Levenberg-M.	MSE	R^2	RMSE	MSE	R^2	RMSE	MSE	R^2	RMSE
Training	277.09428	0.918116	16.64615	215.09381	0.935212	14.66607	5.21030	0.998018	2.282608
Validation	1005.87828	0.653692	31.71558	431.05416	0.840329	20.76184	114.60539	0.901618	10.70539
Testing	392.20681	0.674527	19.80421	634.30917	0.826392	25.18549	721.41140	0.850909	26.8591
Bayesian Reg.									
Training	148.13239	0.938265	12.17097	116.67003	0.956422	10.80139	2.30510	0.999999	1.518256
Validation	0	0	0	0	0	0	0	0	0
Testing	**462.00199**	**0.912738**	**21.49423**	441.74510	0.822015	21.01773	965.60128	0.762952	31.07413
S.C.G.									
Training	477.46718	0.810389	21.85102	292.14561	0.874962	17.09226	180.15162	0.909844	13.42206
Validation	121.16415	0.939298	11.00746	254.97652	0.863374	15.96798	369.69612	0.916574	19.22748
Testing	599.40210	0.705664	24.48269	**595.02369**	**0.884259**	**24.39310**	1399.37841	0.689461	37.40827

Figure 9 shows the response plot for the time series. This graphic is used to validate the network performance. The yellow line represents the errors and the blue line shows the response. The figure displays inputs, outputs and errors versus time. It also indicates which time points were selected for training, testing and validation. From the figure, we can see how the errors are associated with the predicted values, over time. The red points show the test targets and blue points show the training targets. From the figure, we see that there are not high errors of the test targets, except one, which is near 100, and other high errors are training targets. The majority of values are below 50. In general, the model seems to perform adequately.

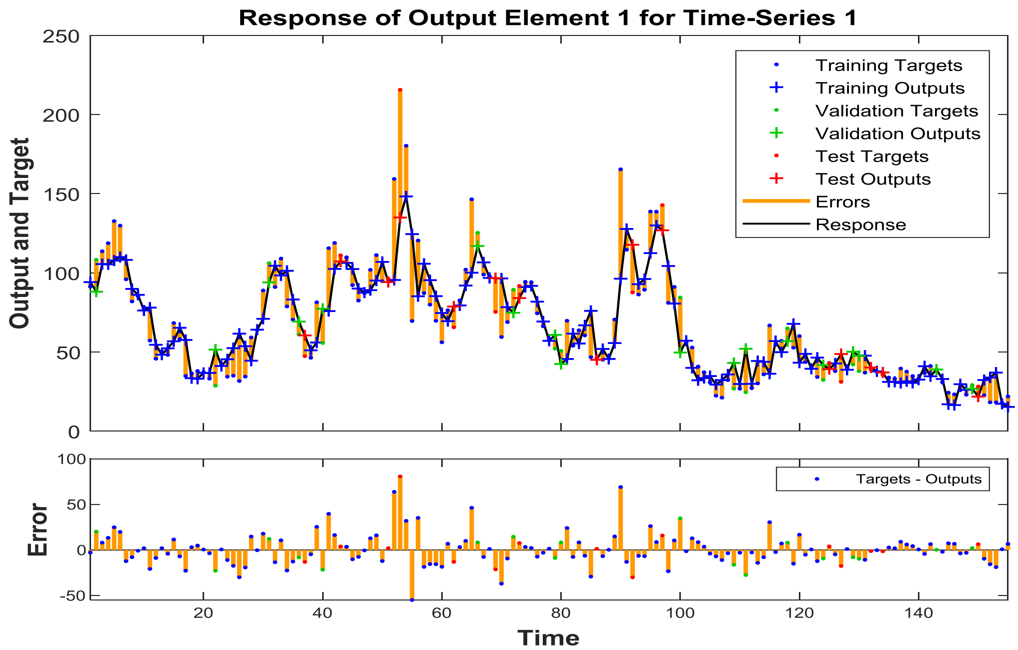


Figure 9: Response plot, batch two, TD1 route.

In the figure 13 in appendix, we see that the training continued until the validation error failed to decrease for six iterations (validation stops). Figure 13 describes the function of error autocorrelation, how the prediction errors are related in time. In a perfect prediction model, there should be only one non-zero value of the autocorrelation function. In a good prediction model, the correlations should fall within the 95% confidence limits around 0. Our model seems to be a bit outside this limit, but in general it is adequate.

Figure 14 represents the regression plot for training, validation and test sets. The closer the data falls along the 45 degree line, the better the fit is. In this case, the R squared are almost 87% for every set, meaning that the fit is reasonably good.

5.2.2. TD2 route: Middle East Gulf to Singapore

Similarly with the TD1 route, the algorithm that provides the best results for batch two variables in the route from the Middle East to Singapore is Scaled Conjugate Gradient. Table 2 shows the MSE, R squared and RMSE values from three algorithms. Their respective values are 899.29, 79.6% and 29.8. We see that the values of the validation set in the Bayesian Regularization are zero, because this algorithm has its own form of validation into the algorithm, and does not require such a dataset. Thus, the validation dataset is disabled by default from the software.

Table 8: Results for TD2 route, three batches and three algorithms

	Batch 1			**Batch 2**			**Batch 3**		
Levenberg-M.	MSE	R^2	RMSE	MSE	R^2	RMSE	MSE	R^2	RMSE
Training	234.75854	0.954769	15.32183	781.52926	0.858411	27.95584	595.45760	0.881383	24.402
Validation	1197.7888	0.809028	34.60909	968.06404	0.772623	31.11372	662.50230	0.625387	25.73912
Testing	3167.8405	0.732716	56.28357	1656.8593	0.546520	40.70453	2445.5716	0.636254	49.45272
Bayesian Reg.									
Training	368.60557	0.924905	19.1991	96.65472	0.980610	9.831313	3.99054	0.999999	1.997634
Validation	0	0	0	0	0	0	0	0	0
Testing	1904.5323	0.653759	43.64095	4106.2195	0.372879	64.07979	3794.7966	0.717692	61.60192
S.C.G.									
Training	643.88391	0.834176	25.37487	989.14457	0.801571	31.45066	594.40228	0.854971	24.38037
Validation	436.32435	0.890508	20.88838	1023.0542	0.560314	31.98521	2035.8179	0.752628	45.12004
Testing	4775.5901	0.523292	69.10564	**889.29513**	**0.796274**	**29.82105**	1286.1977	0.810690	35.8636

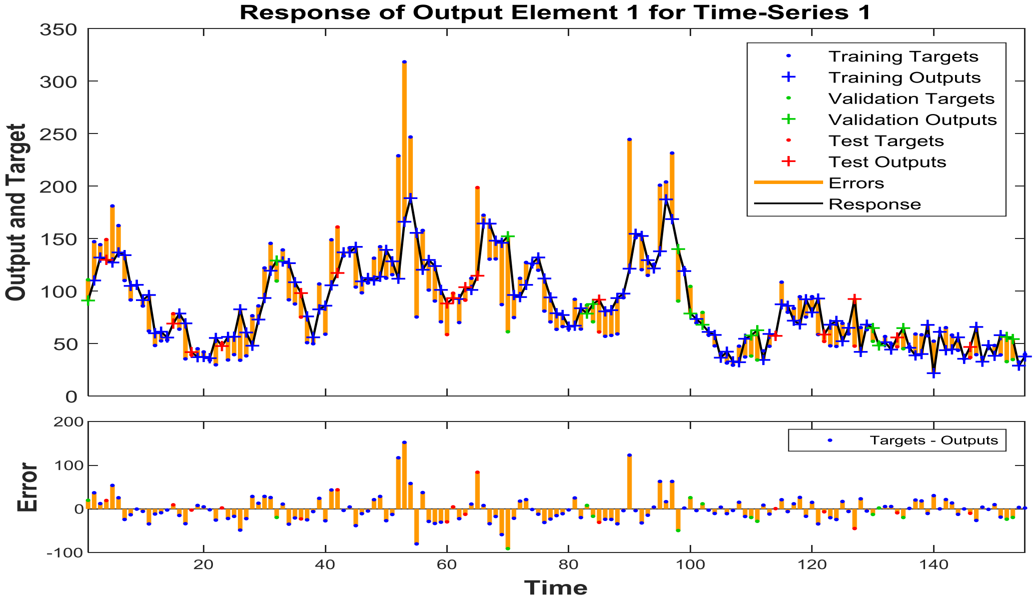


Figure 10: Response plot, batch two, TD2 route.

As we explained in the TD1 route, here we see a similar graph with variability of training, validation and test outputs and targets. In figure 10, we see some more errors in this route, than in TD1 route, which fits also with the lower performance results of RMSE and R squared. The training target errors are higher than those of the test targets

5.2.3. TD6 route: Black Sea to Mediterranean

For the TD6 route, the algorithm that provides the best results for batch 2 variables is Bayesian Regularization. Table 5 shows the error measures for each batch and algorithm. The values of the testing sample for batch 2 with Bayesian Regularization are: MSE = 797.23, R squared = 87% and RMSE = 28.2.

Table 9: Results for TD6 route, three batches and three algorithms.

	Batch 1			Batch 2			Batch 3		
Levenberg-M.	MSE	R^2	RMSE	MSE	R^2	RMSE	MSE	R^2	RMSE
Training	1904.42683	0.758057	43.63974	714.49024	0.907277	26.72995	1804.64325	0.732242	42.48109
Validation	1873.11071	0.590252	43.27945	295.60433	0.899872	17.19314	1637.44786	0.748628	40.46539
Testing	2907.72826	0.496585	53.92336	2963.5771	0.394373	54.43874	1356.82685	0.800335	36.83513
Bayesian Reg.									
Training	1085.96507	0.818458	32.95398	1115.0377	0.840440	33.39218	932.23289	0.854177	30.53249
Validation	0	0	0	0	0	0	0	0	0
Testing	2547.21215	0.834786	50.46991	**797.23664**	**0.870829**	**28.23537**	1692.87577	0.852649	41.14457
S.C.G.									
Training	1786.63413	0.726308	42.2686	2035.40751	0.671113	45.11549	1541.58118	0.760036	39.26297
Validation	1903.87385	0.731781	43.6334	1478.97351	0.426608	38.45742	1606.88549	0.828155	40.08598
Testing	1121.54709	0.778410	33.48951	4648.09227	0.525441	68.17691	2559.88953	0.676706	50.59535

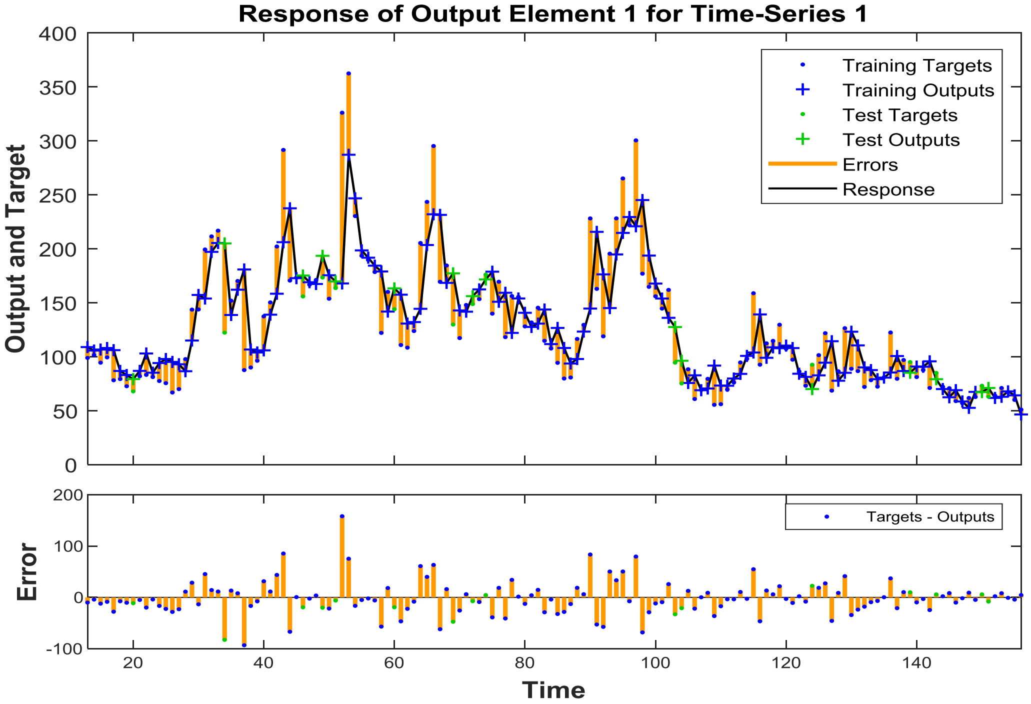


Figure 11: Response plot, batch two, TD6 route.

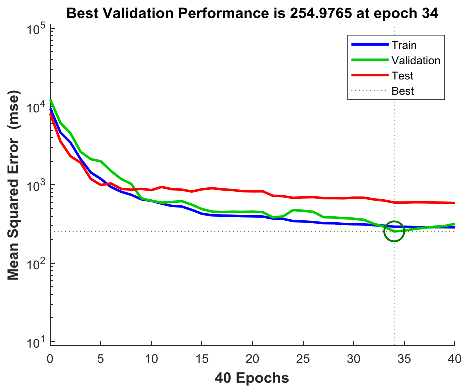
Similar to the two other routes, this graph shows the errors over time. Here, we see a higher value of error which is over 350, but in general there are fewer high errors than the TD2 route.

5.2.4. Performance of all three routes

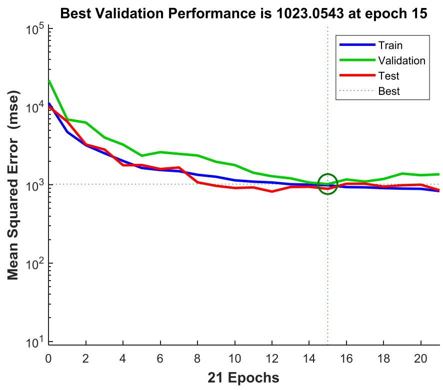
Table 10 shows a summary of the best results for batch two for all three routes, with their respective algorithms and forecasting error measures. Route TD1 offers the best results for the testing sample, with higher value of R squared and lower value of RMSE. As it is concluded in the table, the route that provides the best results of batch two, is TD1 with Scaled Conjugate Gradient model.

Table 10: Results summary table

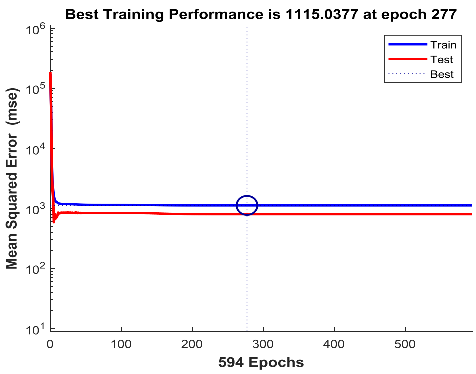
TD1 (SCG)	MSE	R^2	RMSE
Training	292.14561	0.874962	17.09226
Validation	254.97652	0.863374	15.96798
Testing	**595.02369**	**0.884259**	**24.39310**
TD2 (SCG)			
Training	989.14457	0.801571	31.45066
Validation	1023.05425	0.560314	31.98521
Testing	**889.29513**	**0.796274**	**29.82105**
TD6 (Bayesian Reg.)			
Training	1115.03774	0.840440	33.39218
Validation	0	0	0
Testing	**797.23664**	**0.870829**	**28.23537**



(A) TD1



(B) TD2



(B) TD6

Figure 12: Validation performance for three routes

Figure 12 shows the validation performance, where the blue line represents the training mean squared error line, the green line represents the validation and the red line represents the test. A good performance is shown when the last mean square error is small, the test error and validation error have similar line and no significant overfitting or underfitting has occurred by iteration where the best performance happens.
In the TD1 route, the iteration stops at epoch 25 from 40 epochs in total, and the mean error is smaller over time. In the TD2 route, the three sets have similar characteristics, and the iteration has stopped at number 15. In the TD3 route, the train and test set also have similar lines, they follow each other as parallel lines. Based on these, the results and performance seem to be reasonable.
In the figure 19 in Appendix, are shown the error histograms for each route. Blue bars represent training data, green bars represent validation data and the red ones represent testing data. These histograms indicate if there are outliers, or data points where the fit is worse than the majority of data. For the TD1 route, the majority of data fall between the values of -30 and +30 but there is a test point that falls in the value of 70. The two other routes have similar results, but TD6 seems to perform better.

5.2.5. Naïve forecasting results

As stated previously, dynamic naïve forecasting is used as a benchmark for neural network models. We calculated the RMSE measure for the three routes and the results are presented in the table :

Table 11: Naïve forecasting results

Routes	RMSE
TD1	18.6618
TD2	32.3224
TD6	41.6129

6. Discussion

This section discusses the results obtained in the previous section, what the findings mean, their importance and value. Then, it compares them with the theories mentioned previously in the literature review. It discusses their implication for the industry and for further research.

6.1. Discussion of TD1 results

From the results of TD1 route, we see that batch one performs slightly better than batch two, even though the results are quite similar. We chose batch two to generalize the findings for all three routes, keeping the same batch for all the routes.

Scale Conjugate Gradient model outperforms other two models in the batch two variables, where training and validation have similar values with a RMSE around 15 and 17 and R squared around 86%. The testing data had an even better R squared value, even though the RMSE was increased to 24. In general, the results are good, but not perfect.

On the other hand, when we compare the results with our benchmark model, naïve forecasting, we see that the RMSE value is lower in naïve forecasting than in the neural network models. Naïve forecasting is one of the simplest methods, and does not take into consideration explanatory variables that might affect the freight rates, like it is done in neural networks and other advanced models. Still, it shows a lower level of RMSE for the TD1 route. This surprising result is in line with the idea of some previous studies that have shown that sometimes simpler models provide better results. Lyridis et al. (2004), showed that for short term forecasting, naïve outperforms neural networks. This might also be the case in this study.

6.2. Discussion of TD2 results

Results of TD2 route show that Scaled Conjugate Gradient outperforms the two other models, with values of R squared and RMSE respectively 79.6% and 29.8. This route in general does not provide very good results for the three algorithms, where we see that Levenberg-Marquardt and Bayesian Regularization perform much poorer than S.C.G. This might be because the explanatory variables are not the one which mostly influence this route. There might be other important variables that affect it, and might be analyzed and discussed in further research. Neural networks outperform naïve forecasting in this route, with a lower RMSE.

6.3. Discussion of TD6 results

Differently from the two other routes, results of Black Sea to Mediterranean route show that Bayesian Regularization outperforms other models and naïve forecasting too. Still, it shows poorer results than the two other routes. Error measurement values of MSE, RMSE and R squared were higher than in the other routes. An explanation for that could be a higher volatility of the freight rates in this route. The fluctuations of this route have been higher since 2020, when the market was hit by the pandemic and travel restrictions, and still continues. The trend created a falling demand for crude oil from European refineries, especially those located in France, Spain and Italy.

6.4. Summary of three routes results

In general, we see that in two routes, neural networks outperform naïve forecasting. One reason for that could be that tanker freight rates are highly affected by other variables, such those we took into consideration in our study and other variables. Tanker rates are not only affected from previous rates but also from exogenous variables such as crude oil price, fleet development, new-building prices etc.

Regarding the comparison between two ship sizes, we see that VLCC has better forecasting performance than Suezmax, with lower forecasting errors. This implies that the batch two variables might not influence Suezmax as much as they influence VLCC or that VLCC freight rates might be less volatile than those of Suezmax. We remind here that batch two variables include: fleet development, new-building deliveries, demolition, order book, new-building contracts, bunker prices, and crude oil price. If the latter would be true, it might contradict the finding of Kavussanos (1996), who found that price returns in smaller vessels were less volatile than those in larger vessels. Other studies, such as that of Lyridis et al (2004) have used some other variables such as secondhand prices or oil stock building. On the other hand, Lyridis et al (2017), have used also laid-up vessels as an independent variable in their study. Thus, depending on the variables we use, the results and forecasting performance varies too.

6.5. Implication for research

While the latest research on the tanker market have focused a lot on implementing neural networks, as we saw in the literature review section, there are few that has implemented the three models that we used in this study. We see that it is not so necessary to use as many variables as we can, in order to get a good performance. In this case, batch two has seven variables, and performs better than batch three that has more variables. This supports the theory of Molvik & Stafseng (2018) that parsimonious variables outperform variable-rich models.

In general, the results of the study are in line with previous research, because neural networks accuracy level seems to be higher when comparing it with simpler forecasting models such as naïve forecasting or ARIMA model. The literature review section showed that Li & Parsons (1997), found that neural networks perform better than ARIMA models, especially in long-term forecasting.

The results of this study fit also with those of Lyridis et al. (2004), who forecasted VLCC spot rates, and even though they implemented multilayer perceptron networks, they found that neural networks outperform naïve forecasting in 3-months to 12-months forecasting. The period of their analysis was from 1979 until 2002, while this study analyzed the period 2000-2020. This means that the findings are still consistent, and that neural networks can offer improved forecasting for crude oil tanker rates. Fan et al (2013), also supported the findings that for long-term forecasting, ARIMA model performs poorer than neural networks. Levenberg-Marquardt and Bayesian Regularization algorithms as in this study, were used by Jung (2019), but he forecasted the tanker market earnings and found that Bayesian Regularization algorithm performs better. For the 3-months ahead prediction for VLCC, MSE was 8.9 with Bayesian Regularization algorithm and 23.8 with LMA algorithm. Overall, given that here are used different models of neural networks than in previous studies of forecasting oil tanker freight rates, implies that these models are still something new in the tanker market and there might be room for further improved forecasting and research.

6.6. Implication for the industry

These findings might be valuable for the shipping companies that operate in the tanker market, especially for ship owners and charterers. Ship owners need to predict future freight rates in order to analyze their profitability potential, and understand in which ship`s sizes to invest. If the freight rates are predicted to be high, new firms might be attracted to enter the market for the transport in these three routes. On the other hand, charterers need accurate forecasting in order to estimate potential expenses and see if it is worthwhile to time charter a specific ship in a specific route. Both these parties, and other third interested parties can use the information obtained from these results, and predict reasonable future freight rates.

The tanker companies or other tanker market players might use Scaled Conjugate Gradient model or naïve forecasting to make predictions for the route from Middle East Gulf to U.S. Both methods provide similar results. Still, since we compare only one error measure which is RMSE, we cannot fully imply that naïve forecasting is precisely more accurate than S.C.G. Companies might use Scaled Conjugate Gradient model for the route from Middle East to Singapore, and Bayesian Regularization for the route from Black Sea to Mediterranean, as they presented higher accuracy for the specific seven variables of batch 2. In case of other exogenous factors taken into consideration, or other batches of variables, the models also change because they offer different results.

The difference of the results between the two sectors, VLCC and Suezmax, might as well influence maritime investor`s decisions regarding in which tanker ship to invest, and in new-buildings orders. Despite the good forecasting methods, the tanker market, as all other shipping markets, was highly affected from Covid-19 pandemic. Covid-19 travel restrictions negatively affected the demand for crude oil, creating a gap between oil demand and supply. This directly influenced the demand for oil tankers. Unforeseen events like this, make the future even more unknown and make forecasting even more difficult and less reliable.

7. Conclusion

7.1. Conclusion of the main findings

Uncertainty is the center of decision making in the tanker market, therefore making risk calculation is extremely important for companies. Shipping companies need to take rational decisions, to optimize their fleets, by using market knowledge and efficient forecasting models.

First in the study, we did a review of previous literature related to freight rates. Then, we gave a short description of the oil tanker market and the chosen routes. After gaining an insight into the market, we analyzed the driving factors of freight rate fluctuations. We used neural networks to investigate which forecasting model performs better for freight rates in the crude oil tanker market. We chose nine explanatory variables: bunker prices, new-building deliveries, crude oil demand, crude oil price, oil production, fleet development, fleet demolition, tanker order-book and new-building contracts. We divided the data in three batches; first batch has seven variables, in the second batch we add crude oil prices and the third batch includes all nine variables.

Three forecasting models were scrutinized: Levenberg-Marquardt, Bayesian and Scaled Conjugate algorithms. They were generated from machine learning in Matlab software to understand which of the models provides the best results for three tanker routes, TD1, TD2 and TD6. To check the performance we used three accuracy measures: MSE, R^2 and RMSE. Furthermore, we compared the results with those of naïve forecasting, which served as a benchmark.

Two research questions were raised: 1) What are the factors that drive volatility the oil tanker market? 2) Which model can provide an improved forecasting for crude oil tanker freight rates? Regarding the first research question, we analyzed and found that the main factors that affect freight rates demand and supply are: world economy, oil demand and supply, oil prices, oil shocks, climate conditions, seasonality, new-building orders, new-building deliveries, vessel tonnage availability, shipbuilding deliveries, political decisions, repair costs, new reserves and scrapping prices.

Regarding the second research question and the main one of this study, we found the following findings:

- In a route level, batch 1 performs slightly better than other batches for TD1 route. Batch two performs better for the two other routes. Since the difference of the results is almost insignificant, we keep "batch two" as a uniform group of variables in all three routes and compare the three models with each other. For TD1 route, the model that performs best is Scaled Conjugated Gradient model. Still, naïve forecasting offered a slightly higher accurate error measurement of RMSE.
- For TD2 route, the model that performs best is Scaled Conjugated Gradient and the neural networks outperform the naïve forecasting.
- For TD6 route, the model that performs best is Bayesian Regularization and neural networks outperform naïve forecasting.

7.2. Limitations of the study

This study is limited to only two tanker sizes and three routes in total. VLCC and Suezmax were chosen because they are the major ships that transport crude oil in the world. The study could be wider if other ship sizes will be studied further, by employing the same methodology.

The testing sample was divided into the rule of 80-10-10, where 10% was the testing sample, 10% the validation sample and 80% the training sample. This might create a limitation, but further studies can be done to compare results for other training-testing-validation sample

It is also beyond the scope of this study to consider other behavioral factors related to maritime players psychology, but it only uses a quantitative methodology based on historical data.

7.3. Recommendations for further research

We discussed about the high volatility of the tanker freight rates, and how they are directly or indirectly affected from exogenous variables. Based on the findings, we recommend the shipping firms that operate in the route from Middle East to U.S. Gulf (TD1) and to Singapore (TD2) to use Scaled Conjugate Gradient model, in order to make forecasting of future freight rates. The shipping firms that operate in the route from Black Sea to Mediterranean are suggested to use the Bayesian Regularization model, in order to get higher accuracy in their forecasting process.

Further academic studies should take into account other routes, and other ship sizes or other benchmarking models, for a more thorough picture of the whole tanker market. Other models of neural networks can be used and compared with each other, to see which of them all provides best results. In addition, psychological behavioral factors that are related to how shipping players react in the market, play an important role and can be analyzed in more detail in further research. The important is to continuously make new research, to keep updating the tanker market players with new findings and future forecasting techniques that might even more accurate than those already studied, and can make a good contribution for preventing large risks in the market.

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Appendix

Appendix A: Results performance for all routes

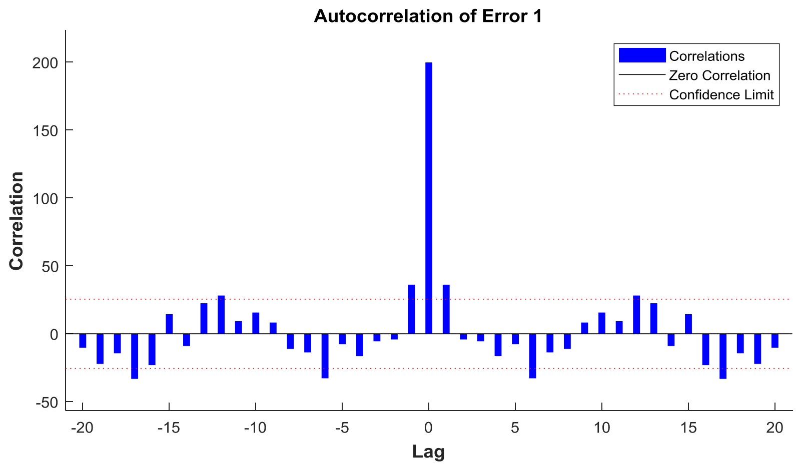


Figure 13: Autocorrelation of error. TD1 route, batch two variables.

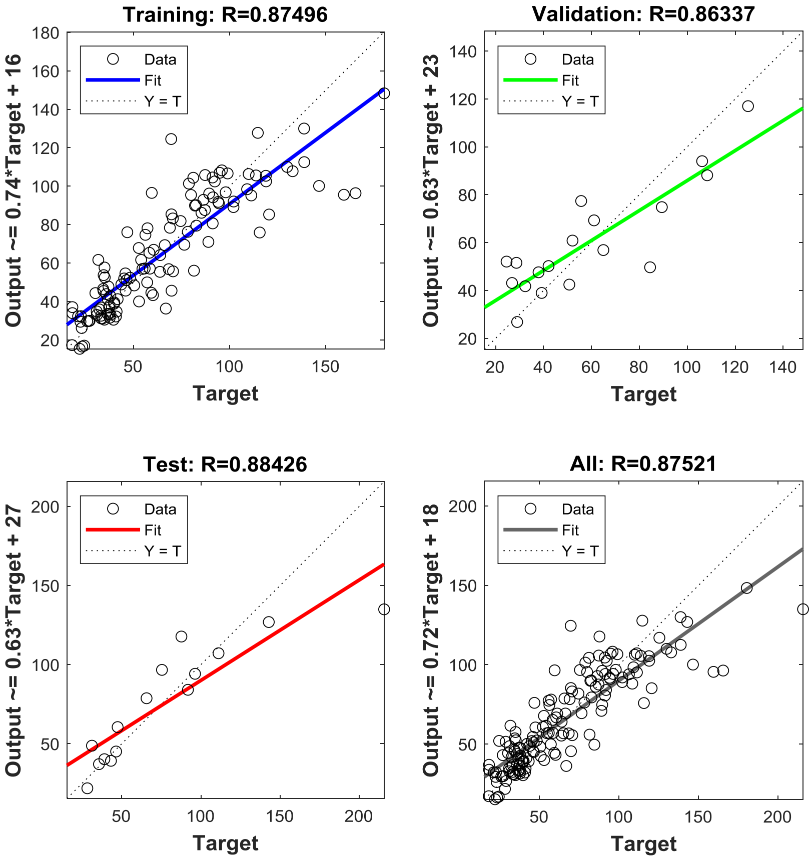


Figure 14: Regression plot

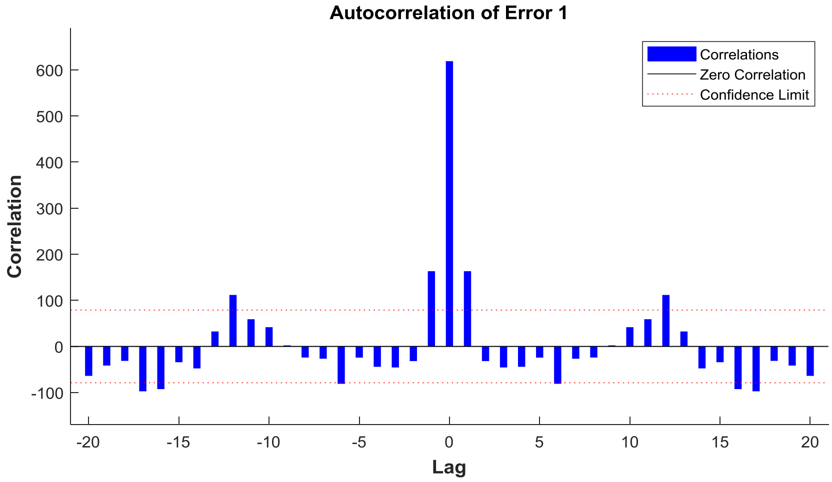


Figure 15: Autocorrelation of error. TD2 route, SCG algorithm.

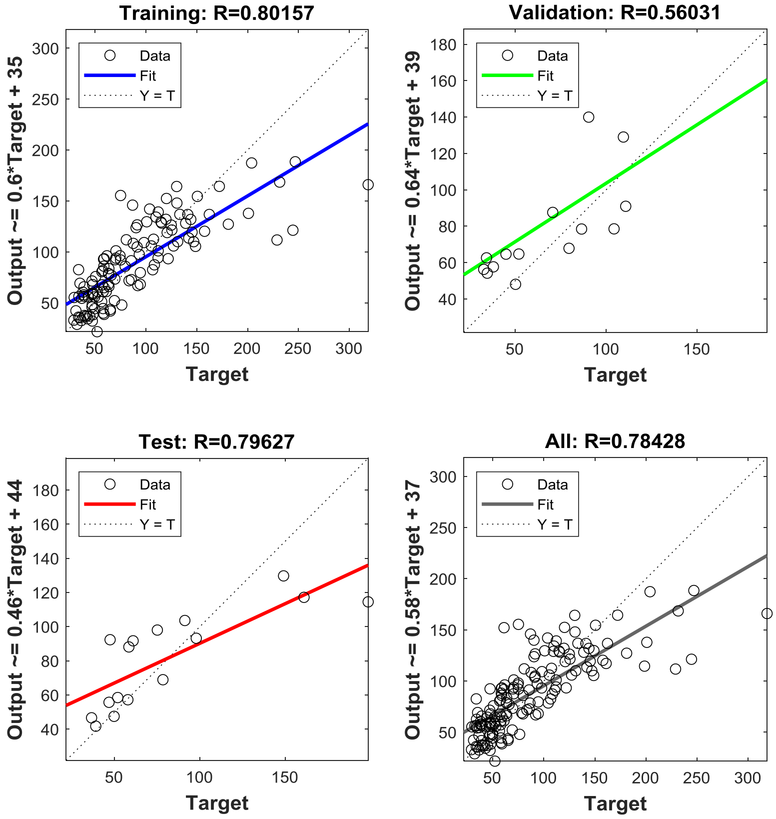


Figure 16: Regression plot. TD2 route, SCG algorithm.

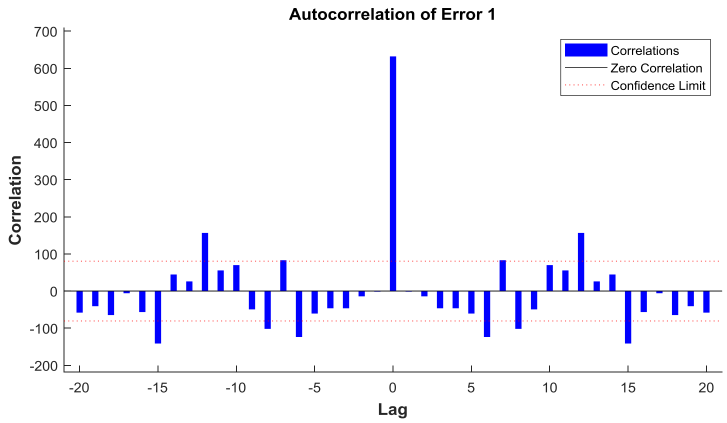


Figure 17: Autocorrelation of error. TD6 route.

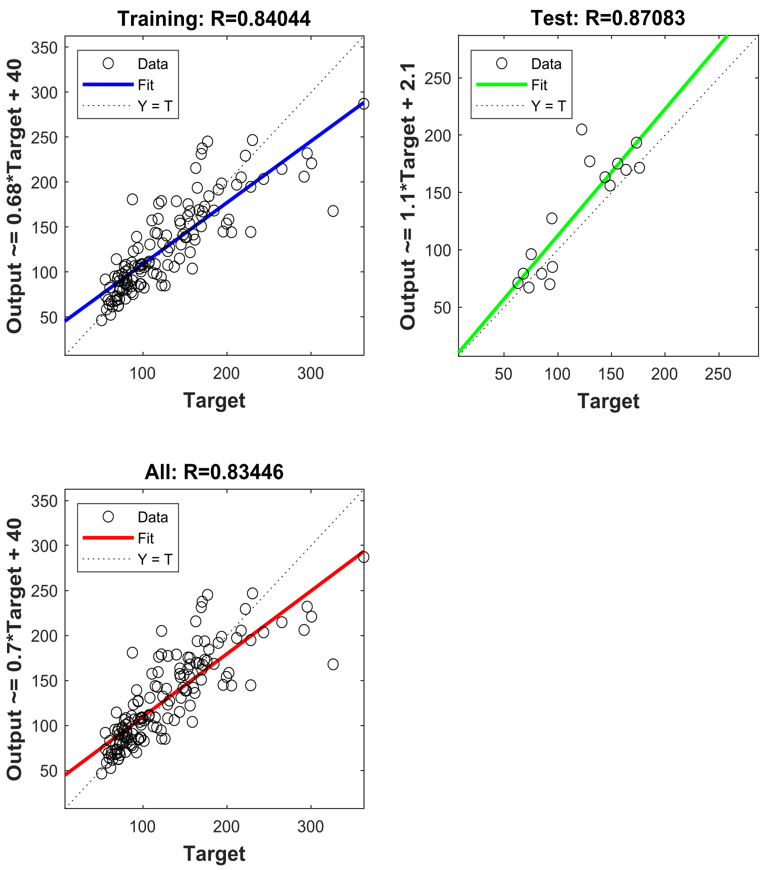
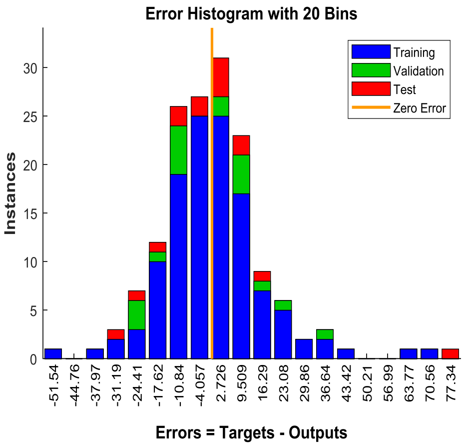
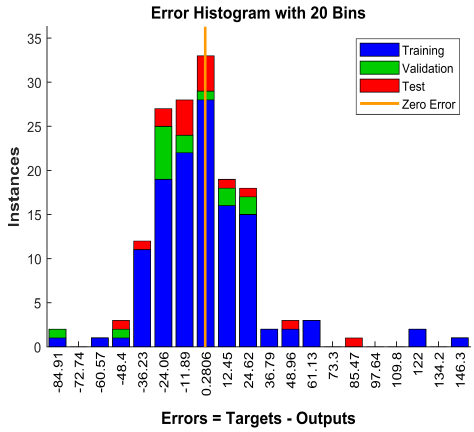


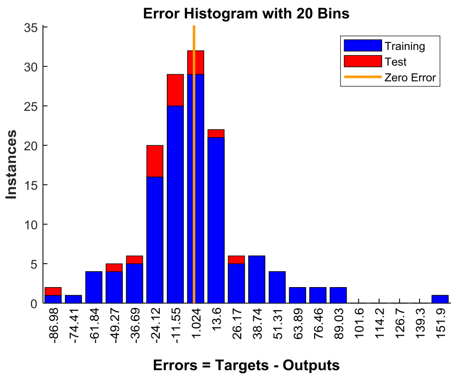
Figure 18: Regression plot. TD6 route.



(a) TD1



(b) TD2



(c) TD6

Figure 19: Error histogram, three routes.