Key Drivers of the Shipping Sector: Comparing Time Series Econometrics and Machine Learning in Predicting Freight Rates and Steel Scrap Prices

Xakousti-Afroditi Merika
National and Kapodistrian University of Athens
Mail: xmerika21@gmail.com

Rafaela-Theodora Merika
Danaos Shipping Management
Mail: rafaelamerika2001@gmail.com

Henry Penikas
Forecasting Dept. Central Bank of Russia
Mail: penikas@gmail.com

ABSTRACT

The shipping industry operates on a global scale, characterized by significant volatility and cyclicality. It facilitates over 80% of global trade by volume and provides employment across countries. This study offers a quantitative exploration of the determinants of dry bulk freight rates (a key profitability metric) and demolition prices (representing the residual value of vessels). The freight and demolition markets are inherently interconnected, and this interdependence is intricately modeled in our proposed framework.

To date, no comprehensive study has simultaneously addressed these two pivotal sectors of the shipping industry with the aim of developing a scientifically grounded predictive mechanism. Such a mechanism is crucial for informed decision-making—specifically, determining whether a shipowner should capitalize on the residual value of a vessel through the demolition market or focus on generating cash flows from the freight market.

Following an extensive review of the literature, which highlights both the strengths and gaps in prior research, we propose and implement an Artificial Neural Network (ANN) model. Using a unique dataset sourced from the Clarkson's database, and the largest demolition shipping company globally, we rigorously test the robustness of our model and benchmark its performance against established econometric models, including ARIMA and VAR. Our findings demonstrate the superior predictive capabilities of the ANN-based approach.

This study is of significant value to both academics and industry practitioners in the maritime sector. It addresses a critical gap in the literature and provides a novel perspective on decision-making. Furthermore, the proposed framework serves as a robust decision-support tool for shipowners and stakeholders worldwide.

1. Introduction

Maritime transport is the backbone of global trade, facilitating the movement of commodities worldwide at competitive costs (Açık and Başer, 2017). Accounting for over 80% of global trade by volume, the shipping industry operates through four interconnected submarkets: the freight market, the newbuilding market, the sales and purchase market, and the demolition market (Stopford, 2001). These submarkets are deeply interdependent, with shifts in one directly influencing the others throughout a vessel's lifecycle.

Among these, the freight market serves as the cornerstone of the maritime sector. It involves the chartering of vessels by cargo owners from shipowners, with freight rates acting as a primary indicator of market health and profitability. These rates are determined by the dynamic balance of supply and demand for transportation services, with fluctuations influenced by global economic conditions, geopolitical events, and operational costs. The cyclicality and volatility of freight rates significantly impact shipowners' revenues and often trigger shifts in the demolition market.

The demolition market, in turn, acts as a regulatory valve for vessel supply, adjusting the fleet size to align with prevailing demand. This market not only recovers valuable materials such as steel scrap but also plays a critical role in balancing the broader shipping industry. For example, during periods of high freight rates, shipowners are incentivized to retain vessels, reducing the supply of steel scrap and driving up demolition prices. Conversely, during periods of low freight rates, increased scrapping activity restores equilibrium, stabilizing freight rates and ensuring sustainability in the sector (Karlis, Polemis, and Georgakis, 2016).

Despite the clear economic significance of ship recycling, existing research often focuses on environmental and regulatory aspects, leaving the economic dynamics of the demolition market underexplored.

This gap is particularly relevant for shipowners, who face complex decisions about whether to continue operating aging vessels or recycle them. These decisions are shaped by factors such as:

1. Economic Obsolescence: When older ships are outperformed by more efficient vessels, reducing profitability (Açık and Başer, 2017).
2. Physical Obsolescence: When maintenance and operational costs for deteriorating ships outweigh potential earnings (Evans, 1989).
3. Political Obsolescence: When regulatory non-compliance renders a ship ineligible for operation (Evans, 1989).

Addressing these challenges requires a robust decision-making framework that integrates insights from both the freight and demolition markets. The strong positive correlation between freight rates and demolition prices (Mikelis, 2007) highlights the interconnected nature of these markets. For instance, high freight rates discourage scrapping, reducing steel scrap supply and driving up prices, while low freight rates result in increased demolition activity, stabilizing the market.

This study aims to develop a decision-support system that leverages Artificial Intelligence (AI) and Machine Learning (ML) techniques to predict the optimal recycling time for ships, thereby maximizing profitability for shipping companies. The system analyzes key driving factors from the freight and demolition markets to provide actionable insights for shipowners, particularly for older dry bulk vessels where recycling decisions are critical.

To achieve this, the study firstly, explores the interdependencies between the freight and demolition markets. Second, identifies the economic and operational factors influencing ship recycling decisions. Third, integrates these factors into predictive models to assess the profitability of different courses of action. By embedding these insights into a data-driven framework, this research seeks to address the complexities of ship recycling and provide a structured approach to navigating the cyclical and volatile nature of the shipping industry.

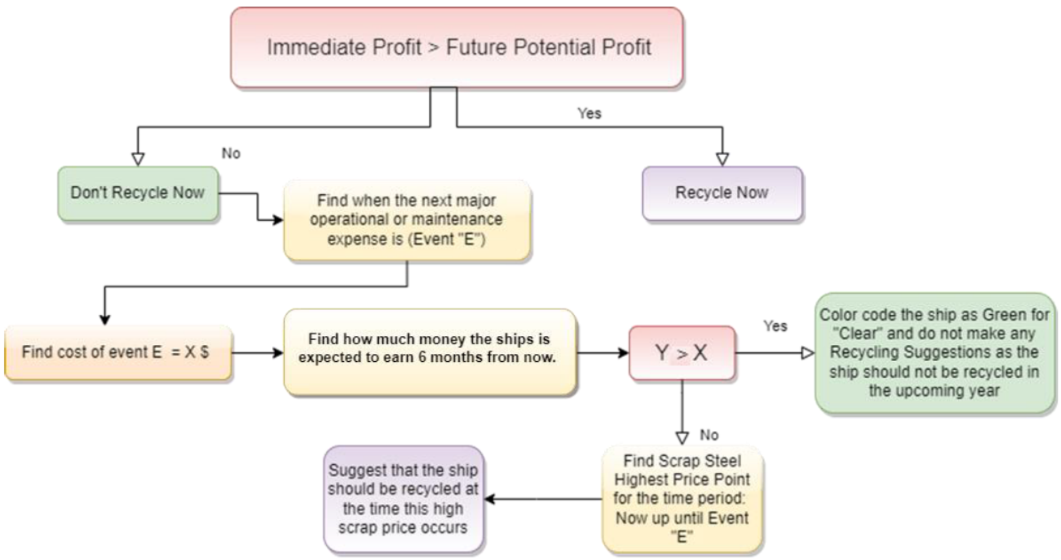
This study not only contributes to bridging the gap in the economic analysis of the demolition market but also offers a practical tool for shipowners to make informed decisions. By doing so, it underscores the broader significance of strategic recycling in maintaining maritime equilibrium and driving long-term sustainability.

In section 2 of this study the system design is described after identifying the needs. Section 3 shows how variables were selected and section 4 introduces methodology and data preparation. Section 5 presents results of our models with respect to the four major dry-bulk indices and the demolition price metrics and compares with VAR and ARIMA models. Section 6 offers concluding remarks.

2. System Design

In the section that follows, we shall describe the design or our proposed system. To clearly define and convey the structure and logical framework of the proposed recycling decision-support system, will begin by offering a brief overview followed by a comprehensive description for each of the system's features which have been broken down into separate smaller tasks. These tasks will be introduced separately, in a sequential order. Below we present a visualization of the proposed system's design.

Logical Framework of the System



The proposed system aims to maximize shipowners' profits, by computing and assessing the optimal future course of actions for a ship. Therefore, for a given demolition decision-making task, the shipowner's future potential profits in each submarket, freight or demolition, are set to be predicted.

2.1 Predicting Freight Rate Levels

This section of the research focuses on understanding dry bulk freight rate dynamics, using the Baltic Dry Index (BDI) as the primary indicator. Beyond representing a weighted average of freight rates in the dry bulk sector, the BDI serves as a critical barometer for global economic activity, influenced by key macroeconomic variables. Literature in this field can be categorized into three distinct strands, each offering unique perspectives on freight rate determination in the dry bulk market.

One significant approach links freight rate determination to macroeconomic variables such as global economic activity, industrial production growth, and oil prices (Hawdon, 1978; Strandenes, 1984; Beenstock & Vergottis, 1989; 1993). Building on this foundation, Tang et al.

(2013) examined shipping cycles in relation to factors such as crude oil prices, inflation, globalization, and dollar exchange rates. Similarly, Lyridis, Manos, and Zacharioudakis (2014) developed forecasting models for the dry bulk market, relying on macroeconomic indicators. In parallel, Batrinca and Cojanu (2014) used an OLS model to analyze freight rates, focusing on supply-demand dynamics and global GDP. Despite certain methodological challenges, their findings aligned with economic theory, highlighting the positive impact of global GDP and the negative influence of ship supply on freight rates.

A second strand emphasizes microeconomic factors. Tamvakis (1995) and Tamvakis and Thanopoulou (2000) linked freight rates to ship-specific characteristics such as age, type, and size. Expanding this approach, Alizadeh and Talley (2011a) identified significant relationships between dry bulk freight rates and vessel attributes, including size, age, lay-can duration, and voyage routes. These insights suggest that individual vessel characteristics could play a pivotal role in decision-making processes, such as ship recycling.

The third strand explores the interaction between commodity pricing and freight rates. Haigh and Bryant (2000) demonstrated that barge rates influence grain prices and market margins. Yu et al. (2007) identified dynamic relationships between corn market prices and freight rates, with disruptions in freight rates significantly impacting corn prices. Kavusanos et al. (2010, 2014) revealed strong endogenous links between commodity and freight derivatives markets, emphasizing the importance of monitoring commodity prices and freight rates due to global economic fluctuations. Angelopoulos et al. (2020) further examined the economic interconnections between globally traded commodities, freight rates, and financial markets, highlighting crude oil prices as a dominant indicator across markets.

Freight rate forecasting gained traction in the 1990s. Early research includes Cullinane’s (1992) application of the Box-Jenkins methodology to forecast the Baltic Freight Index (BFI), demonstrating accuracy using metrics such as RMSE and Theil’s U. Later, Veenstra and Franses (1997) employed a VAR/VECM framework, and Li and Parson (1997) explored neural networks alongside ARIMA models for forecasting, offering groundbreaking insights into non-linear approaches. Neural networks, as noted by Lyridis et al. (2004), excel in capturing sharp market fluctuations, significantly reducing forecast errors.

Subsequent advancements include Wong’s (2014) comparative study of fuzzy heuristic modeling, Grey System, and ARIMA, which concluded ARIMA’s superior performance. Zeng et al. (2015) introduced an EMD-ANN approach, decomposing the BDI into components representing short-term changes, long-term trends, and external shocks, yielding improved forecasting accuracy compared to traditional models.

Drawing insights from these studies, the research proposes employing Machine Learning (ML) models for freight rate forecasting. ML techniques demonstrate considerable promise in this domain, addressing complexities inherent in freight rate dynamics and offering a robust alternative to conventional forecasting methods. By leveraging advancements in this field, the study aims to contribute to more precise and reliable predictive models, aligning with contemporary trends in shipping economics.

2.2 Predicting Steel Scrap Prices

Forecasting steel scrap prices, especially in the context of ship recycling and its driving economic factors, remains an underexplored area in the literature. This section highlights the limited research on this topic and underscores the significance of understanding key determinants to enhance predictive accuracy and decision-making processes.

Karlis et al. (2016) conducted one of the few studies addressing steel scrap price formation. They analyzed the influence of exchange rate fluctuations in countries responsible for over 85% of global ship recycling—India, Bangladesh, Pakistan, and China—against the US dollar. This study detailed the economic transactions involved in recycling ships and highlighted the economic disparity between the developing countries where ships are scrapped and the developed nations housing the largest shipping companies.

Using steel scrap prices as the dependent variable, Karlis et al. modeled price formation through OLS estimation, incorporating factors such as exchange rates, the Baltic Dry Index (BDI) as a proxy for freight rates, and the number of scrapped ships. Their findings revealed that the number of scrapped ships significantly influenced steel scrap prices in the Handysize market segment, while the BDI had a minor positive effect across all models.

Acik and Baser (2017) further explored the cyclical nature of the shipping industry, concluding that a 1% reduction in freight rates leads to a 0.76% increase in the volume of recycled ships. Their findings aligned with those of Karlis et al. (2016), using the BDI as a key indicator of freight market activity. The dependent variable in their model was the volume of scrapped ships, measured in deadweight tonnage (DWT), emphasizing the link between freight rates and ship recycling volumes.

Kagkarakis et al. (2016) employed a VAR model to examine the relationships among steel scrap prices, demolition prices, the number of registered ships older than 20 years, new vessel prices, second-hand vessel prices, and the BDI. They found a particularly strong connection between demolition prices and steel scrap prices. Similarly, Yin (2017) used a Cox proportional hazard model to investigate factors influencing shipowners' decisions to scrap ships. This study categorized variables into two groups: technical characteristics (e.g., ship type, age, and carrying capacity) and market factors (e.g., global GDP and trade balances). Yin and Fan (2018) concluded that market factors exert a greater influence on shipowners' decisions than technical characteristics.

While no definitive conclusion has been reached, it is evident that commodities influence the demand for ships, and consequently, freight rates. Since steel scrap supply depends on freight rates, commodities are an integral consideration in steel scrap price estimation. However, for this study, only "metal" commodities and select market indicators (e.g., Bitcoin value) will be included in the analysis, excluding "agricultural" and "energy" commodities due to dataset limitations.

This research aims to advance the existing literature by identifying key market and ship factors to achieve higher prediction accuracy for freight and steel scrap prices.
Developing and testing a decision-support system to provide a more efficient and reliable framework for determining whether a ship should be recycled.

By integrating these objectives, the study seeks to address gaps in the literature and provide actionable insights for stakeholders in the shipping and recycling industries.

2.3 The ‘Recycle or Not Recycle’ Feature

A central feature of the proposed system is its ability to address the recurring dilemma faced by shipowners: whether to recycle their vessel or continue chartering it. The system evaluates this decision by comparing two key financial outcomes: (1) the immediate recycling profit derived from selling the ship to a scrapyard and (2) the potential future profit generated by continuing to charter the ship over a specific period before reconsidering recycling. By providing clear financial comparisons, the system equips shipowners with actionable insights for making well-informed decisions.

3. Data Description

The dataset used for this research was sourced from Clarkson’s database and spans weekly observations from 1996 to 2022, encompassing 26 variables and totaling 1,404 data points. Although not all variables were consistently recorded throughout the entire period, the dataset remains a highly valuable resource for analysis. This study focuses specifically on two key variables critical to the decision-making process outlined in the model design: freight rate and scrap price.

To identify predictors for the freight rate and scrap price, the Pearson correlation coefficient and Mutual Information (MI) coefficient were employed, as shown in Tables 1 and 2.

The MI coefficient quantifies the mutual dependence between variables, effectively measuring how much information about one variable can be inferred from observing the other. Mathematically, Mutual Information is defined as:

$$I(X;Y) = D_{\mathrm{KL}}(P_{(X,Y)} \| P_X \otimes P_Y) \quad (1)$$

The results of this analysis are presented in Tables 1 and 2. Higher MI scores indicate stronger relationships between independent and dependent variables. In this study, Table 1A focuses on freight rate prices and steel scrap price (Bangladesh Index) as the dependent variables. Variables with MI scores exceeding 0.5, highlighted in the tables, were identified as strong predictor candidates if they had not already been included in the initial selection based on Pearson correlation analysis.

To ensure a robust model, variables with high MI scores were incorporated as predictors for the freight rate and steel scrap price predictive models. Notably, the MI results aligned closely with those of the Pearson correlation analysis. Variables with higher MI scores generally exhibited strong Pearson correlation coefficients as well, reinforcing their suitability for inclusion.

This process of using Mutual Information analysis not only complements the correlation-based approach but also provides an alternative perspective on feature selection, further validating the final set of predictors used in the models.

Based on the notion that, the pandemic immensely affected the dry bulk sector and other shipping subsectors (e.g.: tankers), which is further supported by the majority of studies conducted on this event (Puspa et al., 2021; Gray, 2020; Cullinane and Haralambides, 2021), it was decided that both the freight rate and scrap price predictive models will be considering the monthly Covid-19 cases recorded in China. It should be noted that this is our first successful attempt to incorporate macro-economic exogenous factors in the predictive models that will form the basis of this project's developed ship-recycling decision-support system.

4. Implementation - Methodology

The proposed solution leverages machine learning techniques, specifically neural networks, to address the problem. As with any machine learning project, the success of this approach depends heavily on the availability and careful selection of data features. The system was developed and tested on an Intel(R) Core(TM) i5-6600 4-core CPU @ 3.50 GHz with 16GB RAM, ensuring adequate computational resources for model training and evaluation.

4.1 Why Choose an LSTM Neural Network?

Historically, linear models have been the go-to approach for time series forecasting due to their simplicity, interpretability, and ease of use in straightforward prediction tasks. However, with the increasing availability of market data and advances in deep learning, neural networks have become a focal point for research seeking to solve complex real-world problems.

The choice of neural network architecture depends on the task. For instance:Multilayer Perceptrons (Deep Neural Networks) and Convolutional Neural Networks (CNNs) are commonly used for classification tasks.Recurrent Neural Networks (RNNs) and Recursive Neural Networks excel in language processing tasks.

For time series forecasting, architectures such as Multilayer Perceptrons (MLPs), Recurrent Neural Networks (RNNs), and Long Short-Term Memory (LSTM) Networks are among the most widely adopted (Brownlee, 2022). These networks offer several advantages typical of neural networks, including:Support for multivariate inputs and multi-step outputs.The ability to learn complex mappings between input data and target outputs.The capacity for iterative improvement via the Back-Propagation algorithm, which adjusts weights and biases to enhance prediction accuracy.

RNNs are particularly effective for time series forecasting due to their ability to retain information across time steps using internal memory, known as hidden states. This makes them well-suited for sequential data such as historical price points (e.g., freight and scrap prices). However, RNNs have notable limitations like memory constraints: RNNs struggle to retain information over long sequences, eventually "forgetting" past inputs and computational demands: Their advanced architecture requires longer training times and more complex setup processes.

Given the nature of the shipping industry, characterized by high volatility and long economic cycles averaging six years (Goulielmos, 2020), these shortcomings render traditional RNNs unsuitable for this application.

LSTM Networks Were Selected being a specialized type of RNN, which addresses the memory limitations of traditional RNNs. As their name suggests, LSTMs can effectively manage both short-term and long-term memory, enabling them to capture long-term trends and seasonal patterns in the data. This makes them ideal for modeling the shipping industry, where understanding extended economic cycles and market volatility is crucial.

By utilizing LSTM networks, the system can discover, model, and account for long-term trends in freight and scrap prices, ensuring robust and reliable forecasting for decision-making. This capability, combined with their proven effectiveness in handling sequential data, makes LSTMs the optimal choice for this project.

4.2 Preparing the Data

A crucial preprocessing step in developing the LSTM models was feature scaling, which ensures that variables with different units and numerical ranges do not disproportionately influence the model. Without appropriate scaling, functions in machine learning (ML) algorithms may overly emphasize variables with larger magnitudes while underweighting those with smaller values, potentially leading to biased computations. Feature scaling standardizes numerical ranges, making it easier to identify each feature’s contribution to the dependent variable.

Two common approaches to feature scaling are the Min-Max Scaling and Standard Scaling methods.

The Min-Max Scaler normalizes data to a fixed range, typically between 0 and 1, using the following transformation:

$$X_{scaled} = \frac{x - x_{min}}{x_{max} - x_{min}} \qquad (2)$$

where x represents the original value, and x_{min} and x_{max} are the minimum and maximum values within the feature range. This ensures that the highest values in the dataset remain closer to 1, while the lowest values are mapped closer to 0.

Alternatively, the **Standard Scaler** standardizes data by centering it around zero and scaling it to unit variance, using the formula:

$$X_{stand} = \frac{(x - \bar{x})}{\sigma} \quad (3)$$

Where x is the input value, $\bar{x}$ is the mean and σ is the standard deviation of the training samples (for each column). This transformation is particularly useful for algorithms such as Support Vector Machines (SVM), which assume the data is centered around zero.

The choice between Min-Max Scaling and Standard Scaling is typically data-dependent and requires empirical evaluation. In this study, different scaling techniques were tested to determine their impact on model performance. Ultimately, Min-Max Scaling was selected based on its superior empirical results.

5. Model Architecture

5.1 Layers and Neurons

The structure of the model, including the number of nodes in the hidden layers and the number of hidden layers, requires careful tuning. These hyperparameters are typically determined experimentally, as there is no universal formula for selecting them. To achieve optimal performance, various configurations are tested, and the most effective setup is chosen.

A common heuristic was used as a starting point to determine the number of neurons in the hidden layers:

$$\boldsymbol{Number\ of\ neurons\ in\ a\ hidden\ layer} = \frac{2}{3} \times \boldsymbol{size\ of\ the\ input\ layer} + \boldsymbol{size\ of\ the\ output\ layer}$$

This guideline, widely adopted by machine learning practitioners, provides a reliable baseline for initial experimentation. Subsequent adjustments are made based on the model’s performance during validation.

5.2 Activation Function

Given the time series forecasting nature of the project, the Sigmoid activation function was initially considered. The sigmoid function is expressed as:

$f(x) = \frac{1}{1+e^{-x}}$ (4)

where x is the input to the neuron. This function maps inputs to outputs in the range [0,1], with e^{-x} ensuring positivity and +1 guaranteeing the denominator remains greater than or equal to 1. While sigmoid is widely used in many contexts, it presents notable challenges. Outputs tend to saturate near 0 or 1 for large or small input values, leading to diminished gradients. This results in the vanishing gradient problem during backpropagation, where weights are updated minimally, causing slow or stalled learning and increased computational expense.

To address these issues, the Rectified Linear Unit (ReLU) activation function was explored. ReLU is defined as:

$$f(x)=\max(0, x) \qquad (5)$$

For positive inputs, the function outputs the input value itself, while for non-positive inputs, the output is zero. ReLU offers several advantages that make it highly suitable for deep learning applications. Its simplicity allows for efficient computation, as the calculation involves only the maximum function. By setting negative values to zero, ReLU introduces sparsity in the network, deactivating certain neurons and enhancing computational efficiency.

Another significant advantage of ReLU is its ability to avoid the vanishing gradient problem. The derivative of ReLU is defined as:

$$f'(x) = \begin{cases} 1, if\ x > 0 \\ 0, if\ x \le 0 \end{cases} \qquad (6)$$

Unlike the sigmoid function, ReLU does not produce diminishing gradients for positive inputs, ensuring that weight updates remain effective during backpropagation. This facilitates faster and more robust learning.

Although sigmoid was initially considered due to its historical prominence, ReLU was ultimately chosen for its computational efficiency and ability to mitigate the vanishing gradient problem. This decision supports the goal of achieving a highly performant model architecture suitable for time series forecasting tasks.

5.3 Prediction Accuracy Testing

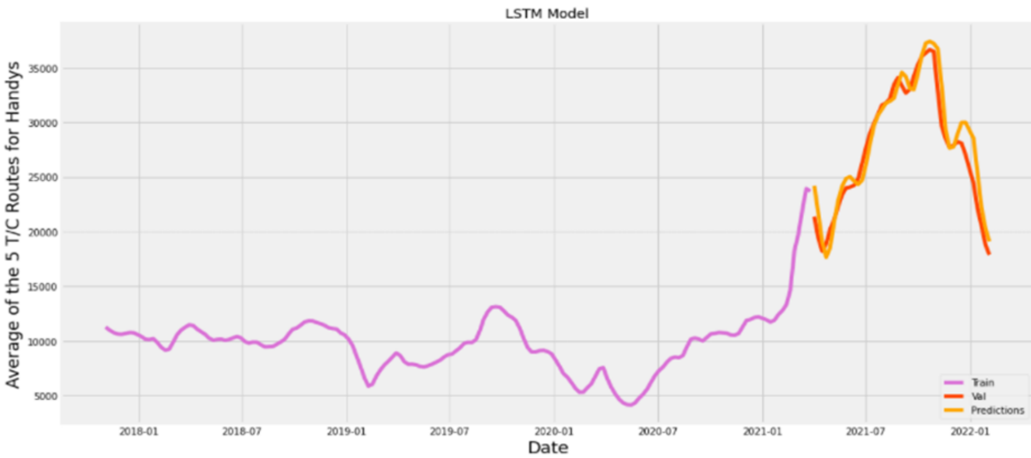
The LSTM Neural Network was employed to forecast dry bulk freight rates for four ship categories: Handysize, Panamax, Capesize, and Supramax. Predictions were made for time intervals of 1 month, 3 months, and 6 months. The following graphs illustrate the model's accuracy compared to the target variables.

Graph 1 presents the LSTM Neural Network's forecast for the 1-month-ahead Handysize freight rate, while Graph 2 displays predictions for the 3-month-ahead interval. Handysize vessels, the smallest in the dry bulk segment, are commonly used to transport grains along major Atlantic and Pacific routes. Between 2018 and 2021, the freight rate trend remained relatively stable, with minimal volatility around its average value. During the COVID-19 pandemic in 2020, rates fell below $5,000—equivalent to the daily operational cost of a vessel of this type. However, starting in February 2021, freight rates surged due to increased demand driven by significant global liquidity injections and persistent supply chain disruptions as the pandemic gradually came under control.

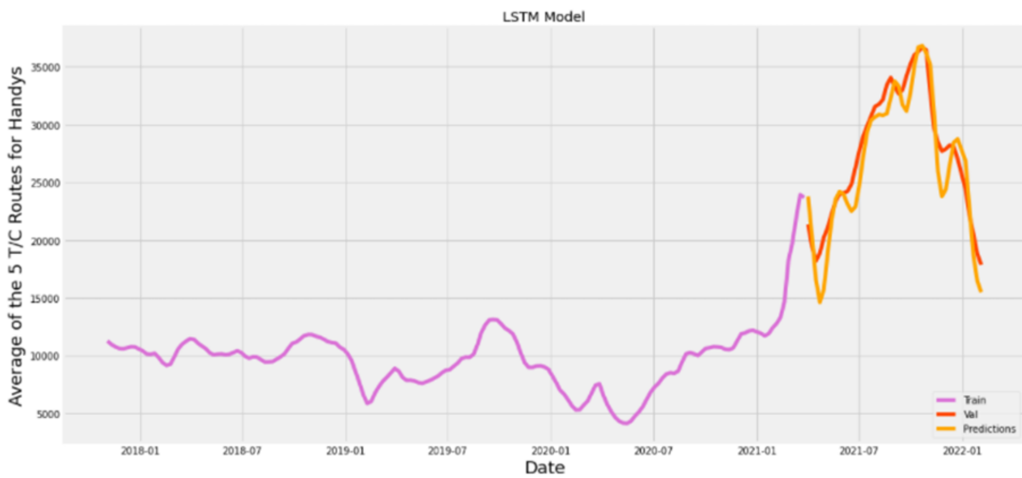
The metrics displayed below each graph confirm expectations: 1-month-ahead predictions are more accurate than 3-month-ahead forecasts. For a highly volatile market like freight, Mean Absolute Percentage Error (MAPE) values of 2.94% for the 1-month interval and 6.75% for the 3-month interval are considered satisfactory.

All forecasted price points shown in this section’s graphs were generated by the LSTM model based on input data from the preceding 36 months. Using this historical data, the model produced predictions for either the next 1 or 3 time steps.

Graph 1: Handysize Freight Rate 1-month ahead prediction interval
RMSE=1,098.5, MAPE=2.94,MAE=1,098.52



Graph 2: Handysize Freight Rate 3-month ahead prediction interval RMSE=1,198.8, MAPE=6.75,MAE=1,214.6



Graph 3 illustrates the LSTM Neural Network's forecast for the 1-month-ahead Capesize freight rate, while Graph 4 presents predictions for the 3-month-ahead interval. Capesize vessels, the largest in the dry bulk sector, are primarily used to transport iron ore and coal along major Atlantic and Pacific shipping routes.

Between 2017 and 2021, freight rates for Capesize ships exhibited the highest volatility among all ship types. During the COVID-19 pandemic (2020 to early 2021), these ships often operated at a substantial loss. However, starting in February 2021, freight rates surged significantly. This increase was driven by soaring global demand for iron ore, a critical construction material, as economic activity in construction reached unprecedented levels. China's GDP growth rate exceeded 8% during this period, and as the world’s second-largest importer of iron ore, the country played a significant role in driving this spike in freight rates.

The metrics displayed below each graph indicate that 1-month-ahead predictions are more accurate than 3-month-ahead forecasts. Although precise accuracy is challenging to achieve in such a highly volatile market, the upward trend in freight rates is captured clearly and approximated effectively by the LSTM model.

Graph 5 depicts the LSTM Neural Network's forecast for the 1-month-ahead Supramax freight rate, while Graph 6 illustrates predictions for the 3-month-ahead interval. Supramax vessels, classified as medium-sized ships, are larger than Handysize but smaller than Panamax. They are primarily used to transport commodities such as fertilizers, grains, bauxite, and steel across major Atlantic and Pacific shipping routes.

Between 2016 and 2021, freight rates for Supramax vessels demonstrated weak profitability, with low rates and average volatility of approximately one standard deviation from the mean during 2016–2020. However, starting in February 2021, freight rates experienced a sharp increase, mirroring trends in other ship types. This rise was driven by a surge in global demand for the commodities transported by Supramax ships.
The metrics displayed below each graph confirm that 1-month-ahead predictions are significantly more accurate than 3-month-ahead forecasts. Despite the inherent volatility in the Supramax market, the prediction accuracy demonstrated by the metrics is satisfactory.

Graph 7 presents the LSTM Neural Network's forecast for the 1-month-ahead Panamax freight rate, while Graph 8 depicts predictions for the 3-month-ahead interval. Panamax vessels, large ships second only to Capesize in size, are more volatile than Supramax and Handysize ships, as reflected in the graphs. These vessels are used to transport iron ore, coal, and steel, typically handling smaller cargo loads compared to Capesize ships, along major Atlantic and Pacific routes.

Between 2017 and 2021, Panamax freight rates displayed disappointing performance, with significant losses recorded during the COVID-19 pandemic. However, from February 2021 onward, freight rates began to recover, following the upward trend seen in Capesize rates, albeit with less intensity.

The metrics shown below each graph indicate that the 1-month-ahead predictions are marginally less accurate than the 3-month-ahead forecasts. Nonetheless, for a highly volatile market like Panamax, the accuracy achieved is considered satisfactory.

The next step involves testing the Bangladesh Steel Scrap Price for 1-month and 3-month prediction intervals. The analysis reveals that the time path of this variable closely aligns with freight rates, as the supply and demand factors influencing the shipping market similarly impact the demolition market. Specifically, when freight rates are high, the number of demolition candidates decreases. Combined with strong demand for steel scrap—the primary raw material for steel production—this dynamic keeps steel scrap prices elevated.

The model demonstrates strong predictive accuracy for steel scrap price formation across all intervals, particularly for the 1-month and 3-month forecasts.

Tables 2 and 3 compare our model's results with ARIMA(3,1,2) and standard VAR(2) models and they are shown to be superior.

Table 2: Freight Comparison Among Models

		ARIMA			VAR			LSTM		
		RMSE	MAPE	MAE	RMSE	MAPE	MAE	RMSE	MAPE	MAE
1 month	Handysize	733.0	2.3	685.0	1,777.4	4.42	1,271.5	1,098.5	2.94	1,098.52
	Panamax	2,992.4	8.2	2,355.5	2,903.2	9.2	2,305.9	1,766.3	5.83	1,995.4
	Capesize	3,897.7	16.6	2,943.2	4,152.5	17.6	3,869.5	286.5	13.6	3,167.3
	Supramax	2,510.0	5.60	1,832.2	5,354.4	19.6	5,176.8	406.2	4.01	484.8
3 month	Handysize	9,780.2	33.8	9,639.5	8,884.0	44.4	8,715.5	1,198.8	6.7	1,214.6
	Panamax	6,498.4	23.3	6,212.9	4,679.3	19.9	4,356.4	2,332.2	5.3	2,897.5
	Capesize	3,023.8	15.2	2,563.3	5,548.8	25.1	5,487.9	298.2	15.8	3,461.9
	Supramax	10,060.5	32.5	9,828.4	11,391.9	59.3	11,173.2	623.15	7.8	872.8
6 month	Handysize	6,411.7	23.6	5,242.3	6,661.7	17.1	5,332.8	2,340.9	12.6	3,592.3
	Panamax	6,132.7	23.6	4,792.9	6,589.3	17.4	5,189.6	1,050.9	5.5	1,892.0
	Capesize	6,846.4	21.7	4,713.5	12,088.4	39.9	11,389.7	1,129.6	24.8	12,279.2
	Supramax	6,095.4	22.3	4,833.9	6,537.8	17.3	5,265.5	1,407.6	15.0	4,745.2

Table 3: Steel Scrap Price Comparison Among Models

Bangladesh Steel Scrap price	**ARIMA**			**VAR**			**LSTM**		
	RMSE	MAPE	MAE	RMSE	MAPE	MAE	RMSE	MAPE	MAE
1 month	10.2	1.50	10.1	24.3	2.90	20.9	9.90	1.41	10.0
3 months	41.0	6.10	40.9	37.8	5.90	37.4	4.84	2.23	14.7
6 months	23.1	3.30	21.6	23.2	3.30	20.6	22.5	2.27	21.2

6. Conclusion

Maritime transport serves as the cornerstone of global trade, with over 80% of goods by value (UNCTAD, 2021) transported via sea. Understanding the factors influencing freight rate and commodity price formation is essential for all stakeholders in the shipping industry. Shippers, investors, policymakers, and even consumers stand to benefit from the insights generated by the decision-making support system proposed in this research. This system aims to enhance decision-making processes, fostering better strategies and outcomes across the maritime and trade sectors.

The demolition market, an integral yet often overlooked component of the shipping industry, exhibits complex interdependencies with freight rates. While this relationship may appear straightforward, it demands deeper investigation to uncover the nuanced dynamics at play.

Inspired by the literature (Angelopoulos et al., 2020), this study has developed a robust framework incorporating a diverse range of commodity drivers that have proven effective in influencing freight and scrap price determination. Additionally, the research has produced and validated forecasting models that outperform both naïve and sophisticated benchmarks, such as VAR and ARIMA, in terms of accuracy and reliability.

Looking ahead, we propose expanding the research by integrating the current system with other advanced algorithms, such as Broyden (Mohd et al., 2014), Gauss-Seidel, and Newton methods (Ludwig, 2007). These algorithms could enhance the system's capability to simulate macroeconomic scenarios and assess their impacts on forecasting models. Another compelling direction involves exploring the system's potential to predict economic turning points, such as the 2008 financial crisis, which devastated the shipping industry.

Such advancements would enable the system to assign probabilities to potential turning points, offering invaluable foresight for stakeholders. This is particularly critical in the current landscape, where scrap prices are at two standard deviations above their long-term mean—a significant deviation warranting further analysis. By incorporating macroeconomic scenarios and probabilistic modeling, the system could become a powerful tool for navigating uncertainties in the maritime and demolition sectors, thereby contributing to more resilient and informed decision-making.

References

Acik, A. and Baser., S. (2017) ‘The Relationship Between Freight Revenues and Vessel Disposal Decisions’. Ekonomi Politika & Finans Araştırmaları Dergisi, 2(2) pp. 96-112. Available from: https://doi.org/10.30784/epfad.363721 (Accessed 6 May 2022)

Agraval, S. (2019) ‘The Role Of A Cash Buyer in Ship Recycling’. Marine Insight [Online]. Available at: https://www.marineinsight.com/careers-2/the-role-of-a-cash-buyer-in-ship-recycling/ (Accessed 6 May 2022)

Alizadeh, A., and Talley, W. (2011). ‘Microeconomic Determinants of Dry Bulk Shipping Freight Rates and Contract Times’. Transportation, 38(3), pp. 561-579. Available from: https://link.springer.com/content/pdf/10.1007/s11116-010-9308-7.pdf (Accessed 6 May 2022)

Angelopoulos, J., Sahoo, S., and Visvikis, I. (2020) ‘Commodity and Transportation Economic Market Interactions Revisited: New Evidence from a Dynamic Factor Model’. Transportation Research Part E: Logistics and Transportation Review, 133, pp. 1-15 Available from: https://doi.org/10.1016/j.tre.2019.101836 (Accessed 6 May 2022)

Batrinca, G. and Cojanu, G. (2014) ‘The Determining Factors of the Dry Bulk Market Freight Rates’. Paper presented at the 2014 International Conference on Economics, Management and Development, pp. 109-112. Available from: http://www.inase.org/library/2014/interlaken/bypaper/ECON/ECON-14.pdf (Accessed 6 May 2022)

Beenstock, M. and Vergottis, A. (1993). Econometric Modelling of World Shipping. London: Chapman and Hall.

Beenstock, M., and Vergottis, A . (1989) ‘An Econometric Model of the World Tanker Market’. Journal of Transport Economics and Policy, 23 (3), pp. 263- 280. Available from: http://www.jstor.org/stable/20052891 (Accessed 6 May 2022)

Branch, A., and Robarts, M. (2014). Branch's Elements of Shipping. 9th Edition. New York Routledge.

Brownlee, J. (2022) ‘Deep Learning for Time Series Forecasting’. Machine Learning Mastery [Online]. Available from: https://machinelearningmastery.com/deep-learning-for-time-series-forecasting/ (Accessed 6 May 2022)

Buxton, I. (1991) ‘The Market for Ship Demolition’. Maritime Policy & Management, 18(2), pp. 105-112. Available from: https://doi.org/10.1080/03088839100000034 (Accessed 6 May 2022)

Carrie, B. (2021) ‘FOCUS: India Mulls Over Self-Sufficient Future Without Imported Scrap’.

Clarksons (2022) ‘World Fleet Register’. Clarkson Research [Online]. Available at: https://www.crsl.com/acatalog/world-fleet-register.html (Accessed 6 May 2022)

Cullinane, K. (1992). ‘A Short-Term Adaptive Forecasting Model for BIFFEX Speculation: A Box—Jenkins Approach’. Maritime Policy & Management, 19(2), pp. 91-114. Available from: https://doi.org/10.1080/03088839200000018 (Accessed 6 May 2022)

Cullinane, K. and Haralambides, H. (2021) ‘Global Trends in Maritime and Port Economics: the COVID-19 Pandemic and Beyond’. Maritime Economic and Logistics, 23, pp. 369-380. Available from: https://doi.org/10.1057/s41278-021-00196-5 (Accessed 6 May 2022)

Davydova, O. (2017) ‘7 Types of Artificial Neural Networks for Natural Language Processing’. Medium [Online]. Available at: https://medium.com/@datamonsters/artificial-neural-networks-fornatural-language-processing-part-1-64ca9ebfa3b2 (Accessed 6 May 2022)

Det Norske Veritas (2015) ‘How to Optimize your OPEX’. DNV Group [Online]. Available at: https://www.dnv.com/maritime/how-to-optimize-your-opex.html (Accessed 6 May 2022)

Erol, E. and Dursun, A. (2016) ‘Market Structure and Evaluation of Irregular Line Sea Freight’. International Journal of Economic & Administrative Studies, 16, pp. 153-170. (Accessed 6 May 2022)

Goulielmos, A. (2020) ‘An Anatomy of Cycles in Shipping Industry, 1946-2020’. Modern Economy, 11(10), pp. 1671-1695. Available from: https://www.scirp.org/journal/paperinformation.aspx?paperid=103851 (Accessed 6 May 2022)

Haigh, M., and Bryant, H. (2000) ‘The Effect of Barge and Ocean Freight Price Volatility in International Grain Markets’. Agricultural Economics, 25(1), pp. 41-58. Available from: https://doi.org/10.1111/j.1574-0862.2001.tb00234.x (Accessed 6 May 2022)

Hawdon, D. (1978) ‘Tanker Freight Rates in the Short and Long Run’. Applied Economics, 10, pp. 203-217. Available from: https://doi.org/10.1080/758527274 (Accessed 6 May 2022)

Holloway Houston (2018) ‘Importance of Construction Industry in the Economy and Use of Construction Equipments’. Holloway Houston Inc. [Online]. Available at: https://www.hhilifting.com/importance-of-construction-industry-in-the-economy-and-use-ofconstruction-equipments/ (Accessed 6 May 2022)

ISRI (2020) Scrap Recycling Industry Yearbook 2019. Institute of Scrap Recycling Industries [Online]. Available at: https://www.isri.org/recycling-commodities-old/recycling-industry-yearbook (Accessed 6 May 2022)

Jugovic, A., Komadina, N., and A., Hadzic (2015) ‘Factors Influencing the Formation of Freight Rates on Maritime Shipping Markets’. Scientific Journal of Maritime Research, 29, pp. 2923-2929. Available at: https://www.researchgate.net/publication/284170614_Factors_influencing_the_formation_of_freight_rates_on_maritime_shipping_markets (Accessed 6 May 2022)

Kagkarakis, N., Merikas, A., and Merika, A. (2016) ‘Modelling and Forecasting the Demolition Market in Shipping’. Maritime Policy & Management, 43, pp. 1021-1035. Available from: https://doi.org/10.1080/03088839.2016.1185181 (Accessed 6 May 2022)

Karlis, T., Polemis, D., and Georgakis, A. (2016) ‘Ship Demolition Activity: An Evaluation of the Effect of Currency Exchange Rates on Ship Scrap Values’. Spoudai, 66(3), pp. 53-70. Available from: https://spoudai.unipi.gr/index.php/spoudai/article ... 9/2551-3037-1-SM.pdf (Accessed 6 May 2022)

Kavussanos, M., Visvikis, I., and Dimitrakopoulos, D. (2010) ‘Information Linkages Between Panamax Freight Derivatives and Commodity Derivatives Markets’. Maritime Economics & Logistics, 12(1), pp. 91-110. Available from: https://doi.org/10.1057/mel.2009.20 (Accessed 6 May 2022)

Kavussanos, M., Visvikis, I., and Dimitrakopoulos, D. (2014) ‘Economic Spillovers Between Related Derivatives Markets: The Case of Commodity and Freight Markets’. Transportation Research Part E: Logistics and Transportation Review, 68, pp. 79-102. Available from: https://doi.org/10.1016/j.tre.2014.05.003 (Accessed 6 May 2022)

Lyridis, D., Manos, N., and Zacharioudakis, P. (2014). ‘Modeling the Dry Bulk Shipping Market using Macroeconomic Factors in addition to Shipping Market Parameters via Artificial Neural Networks’. International Journal of Transport Economics, 41(2), pp. 231-254. Available from: https://www.jstor.org/stable/43740977 (Accessed 6 May 2022)

Lyridis, D., Zacharioudakis, P., Mitrou, P., and Mylonas, A. (2004) ‘Forecasting Tanker Market Using Artificial Neural Networks’. Maritime Economics & Logistics, 6(2), pp. 93-108. Available from: https://doi.org/10.1057/palgrave.mel.9100097 (Accessed 6 May 2022)

McConville, J. (1999). Economics of Maritime Transport, Theory and Practice. London: Witherby & Company Ltd.

Mikelis, N. (2013) ‘Ship Recycling Markets and the Impact of the Hong Kong Convention’. Paper presented at the International Conference on Ship Recycling, World Maritime University. Available from: https://issuu.com/worldmaritimeuniversity/docs/mikelis_-_ship_recycling_markets_an (Accessed 6 May 2022)

Morecambe Metals (2018) ‘Metals and Their Properties: Steel’. Morecambe Metals [Online]. Available at: https://www.morecambemetals.co.uk/metals-and-their-properties-steel/ (Accessed 28 October 2021)

NGO Shipbreaking Platform (2019) ‘Cash Buyers’. NGO Shipbreaking Platform [Online]. Available at: https://shipbreakingplatform.org/our-work/the-problem/cash-buyers/ (Accessed 6 May 2022)

Paris MoU (2021) ‘List of Paris MoU Deficiency Codes’. Paris MoU [Online]. Available at: https://www.parismou.org/list-paris-mou-deficiency-codes (Accessed 6 May 2022)

Paris MoU (2021) ‘Memorandum’. Paris MoU [Online]. Available at: https://www.parismou.org/inspections-risk/library-faq/memorandum (Accessed 6 May 2022)

Peterson, S. and Flanagan, A. (2020) ‘Neural Network Hedonic Pricing Models in Mass Real Estate Appraisal’. Journal of Real Estate Research, 31(2), pp. 147-164. Available from: https://doi.org/10.1080/10835547.2009.12091245 (Accessed 6 May 2022)

Placek, M. (2022) ‘Number of Ships in the World's Leading Container Ship Operators' Order Books as of April 30, 2022’. Statista [Online]. Available at: https://www.statista.com/statistics/197675/orderbook-ships-of-worldwide-leading-container-shipoperators-in-2014/ (Accessed 6 May 2022)

Porter, M. (1990) ‘The Competitive Advantage of Nations’. Harvard Business Review [Online]. Available at: https://hbr.org/1990/03/the-competitive-advantage-of-nations (Accessed 6 May 2022)

Puspa, N., Majid, M., Tan, J., Nizam, Z., Kaur, C., Jamal, N., and Leng, C. (2021) ‘The Impact of COVID19 Pandemic on Malaysia’s Maritime Sectors and Way Forward’. Maritime Institute of Malaysia [Online].

Saini, S. (2020) ‘Walmart Taking a Giant Leap Towards Data Analytics and Supply Chain Analytics’.

Medium [Online]. Available at: https://medium.datadriveninvestor.com/walmart-taking-a-giantleap-towards-data-analytics-and-supply-chain-analytics-2c48c9e38f9d (Accessed 1 November 2021)

Salman, A., Heryadi, Y., Abdurahman, E., and Suparta, W. (2018) ‘Single Layer & Multi-layer Long Short-Term Memory (LSTM) Model with Intermediate Variables for Weather Forecasting’. Procedia Computer Science, 135, pp. 89-98. Available from: https://www.sciencedirect.com/science/article/pii/S187705091831439X (Accessed 6 May 2022)

Salman, A., Kanigoro, B. and Heryadi, Y. (2015) ‘Weather Forecasting Using Deep Learning Techniques’. Paper presented at the International Conference on Advanced Computer Science and Information Systems, pp. 281-285. Available from: https://ieeexplore.ieee.org/abstract/document/7415154 (Accessed 6 May 2022)

Scarci, R. (2007) ‘The Bulk Shipping Business: Market Cycles and Shipowners’ Biases’. Maritime Policy & Management, 34(6), pp. 577-590. Available at: https://doi.org/10.1080/03088830701695305 (Accessed 6 May 2022)

Schneekluth, H. and Bertram, V. (1998) ‘Main Dimensions and Main Ratios’. Chapter cited in Ship Design for Efficiency and Economy. 2nd ed. Oxford: Butterworth-Heinemann, pp. 1-33. Available from: https://doi.org/10.1016/B978-075064133-3/50001-3 (Accessed 6 May 2022)

Sea Place (2020) ‘Ship Maintenance Cost: How Can Owners Reduce It?’. Sea Place SL [Online]. Available at: https://www.seaplace.es/maintenance-cost-how-can-owners-reduce-it/ (Accessed 6 May 2022)

Sea Place (2020) ‘Ship Maintenance Cost: How Can Owners Reduce It?’. Sea Place SL [Online]. Available at: https://www.seaplace.es/maintenance-cost-how-can-owners-reduce-it/ (Accessed 6 May 2022)

Ship Inspection (2022) ‘What Costs are Included in “Running Costs” or “Vessel Operating Expenses”?’. Ship Inspection [Online]. Available at: http://shipinspection.eu/what-costs-areincluded-in-running-costs-or-vessel-operating-expenses/ (Accessed 6 May 2022)

Siewers, H. (2020) ‘Key Factors to Consider When Assessing Lay-Up Options’. DNV Group [Online]. Available at: https://www.dnv.com/expert-story/maritime-impact/Key-factors-to-consider-whenassessing-lay-up-options.html (Accessed 6 May 2022)

Sims, C. (1980) ‘Macroeconomics and Reality’. Econometrica, 48(1), pp. 1–48. Available from: https://doi.org/10.2307/1912017 (Accessed 6 May 2022)

Sims, C., Stock, J., and Watson M. (1990) ‘Inference in Linear Time Series Models with Some Unit Roots’. Econometrica, 58(1), pp. 113-144. Available from: https://doi.org/10.2307/2938337 (Accessed 6 May 2022)

SteelConstruction.info (2022) ‘Recycling and Reuse’. SteelConstruction.info [Online]. Available at: https://www.steelconstruction.info/Recycling_and_reuse (Accessed 6 May 2022)

Strandenes, S. (1984) ‘Price Determination in the Time Charter and Secondhand Markets’. Center for Applied Research, Norwegian School of Economics and Business Administration, Working Paper, pp. 1-47. Available from: https://www.econbiz.de/Record/price-determination-in-the-time-charter-andsecond-hand-markets-pettersen-strandenes-siri/10002642295 (Accessed 6 May 2022)

Tamvakis, M., and Thanopoulou, H. (2000) ‘Does Quality Pay? The Case of the Dry Bulk Market’. Transportation Research Part E: Logistics and Transportation Review. 36(4), pp. 297-307. Available from: https://doi.org/10.1016/S1366-5545(00)00005-3 (Accessed 6 May 2022)

Teekay (2016) ‘What is Dry-Docking and Why Do We Do It?’. Teekay Corporation [Online]. Available at: https://www.teekay.com/blog/2016/04/18/step-step-glimpse-dry-docking-process/ (Accessed 6 May 2022)

Textor, C. (2022) ‘China's Share of Global Gross Domestic Product (GDP) Adjusted for PurchasingPower-Parity (PPP) From 2011 to 2021 With Forecasts Until 2027’. Statista [Online]. Available at: https://www.statista.com/statistics/270439/chinas-share-of-global-gross-domestic-product-gdp/ (Accessed 6 May 2022)

Townsend, J. (2017) ‘OPEX – The Ship Management View’. V.Ships [Online]. Available at: https://silo.tips/download/opex-the-ship-management-view-vships (Accessed 6 May 2022)

UNCTAD (2021) Review of Maritime Transport. United Nations Conference on Trade and Development [Online]. Available from: https://unctad.org/system/files/officialdocument/rmt2021_en_0.pdf (Accessed 6 May 2022)

UNCTD (2014) ‘Review of Maritime Transport 2014’. United Nations Conference on Trade and Development [Online]. Available at: https://unctad.org/system/files/officialdocument/rmt2014_en.pdf (Accessed 6 May 2022)

Vadapalli, P. (2021) ‘How Netflix Uses Machine Learning & AI For Better Recommendation?’. upGrad [Online]. Available at: https://www.upgrad.com/blog/how-netflix-uses-machine-learning/ (Accessed 1 November 2021)

Veenstra, A., and Franses, P. (1997) ‘A Co-Integration Approach to Forecasting Freight Rates in the Dry Bulk Shipping Sector’. Transportation Research Part A: policy and practice, 31(6), pp. 447-458. Available from: https://doi.org/10.1016/S0965-8564(97)00002-5 (Accessed 6 May 2022)

Weihs, G., Kumar, K., and D. Wiley (2014) ‘Understanding the Economic Feasibility of Ship Transport of CO2 within the CCS Chain’. Energy Procedia, 64, pp. 2630-2637. Available from: https://doi.org/10.1016/j.egypro.2014.11.285 (Accessed 6 May 2022)

Wong, H. (2014) ‘BDI Forecasting Based on Fuzzy Set Theory, Grey System and ARIMA’. Paper presented at the International Conference on Industrial, Engineering and Other Applications of Applied Intelligent Systems, pp. 140-149. Available from: https://doi.org/10.1007/978-3-319-07467-2_15 (Accessed 6 May 2022)

Worldsteel (2021) Steel Recycling. Wordsteel Association [Online] Available at: https://www.worldsteel.org/steel-by-topic/sustainability/materiality-assessment/recycling.html (Accessed 28 October 2021)

Yang, Y., Raipala, K. and Holappa, L. (2013) ‘Ironmaking’. Chapter cited in Treatise on Process Metallurgy, Volume 3: Industrial Processes. Elsevier Science, pp.2-88. Available from: https://doi.org/10.1016/B978-0-08-096988-6.00017-1 (Accessed 6 May 2022)

Yin, J., and Fan, L. (2018) ‘Survival Analysis of the World Ship Demolition Market’. Transport Policy, 63, pp. 141-156. Available from: https://doi.org/10.1016/j.tranpol.2017.12.019 (Accessed 6 May 2022)

Yu, T., Bessler, D., and Fuller, S. (2007) ‘Price Dynamics in US Grain and Freight Markets’. Canadian Journal of Agricultural Economics, 55(3), pp. 381-397. Available from: https://doi.org/10.1111/j.1744-7976.2007.00098.x (Accessed 6 May 2022)

Zeng, Q., Qu, C., Ng, A., and Zhao, X. (2016) ‘A New Approach for Baltic Dry Index Forecasting Based on Empirical Mode Decomposition and Neural Networks’. Maritime Economics & Logistics, 18(2), pp. 192-210. Available form: https://doi.org/10.1057/mel.2015.2 (Accessed 6 May 2022)

Zhang, J. (2017) ‘Multivariate Analysis and Machine Learning in Cerebral Palsy Research’. Frontiers in Neurology, 8(715), pp. 1-13. Available from: https://www.frontiersin.org/articles/10.3389/fneur.2017.00715/full (Accessed 6 May 2022)

ANNEX.

Tables.

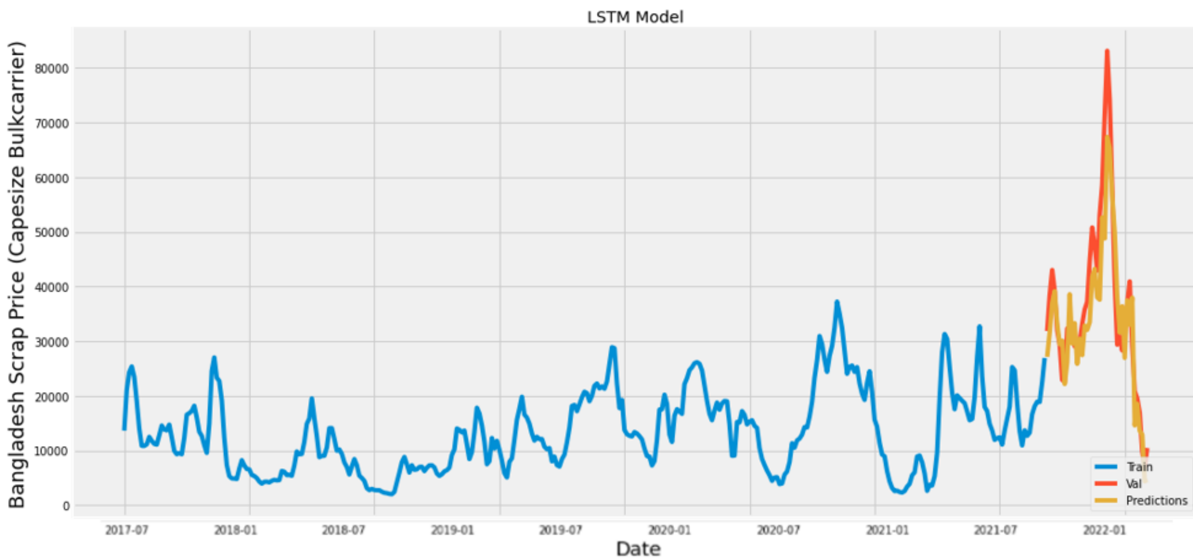
Table 1A. Dependence indicators.

	Dependent Variable			
	Freight Rate		Steel Scrap	
Independent Variable	**Mutual Information Score**	**Pierson Correlation Coefficient**	**Mutual Information Score**	**Pierson Correlation Coefficient**
Copper Price	2,09	0.63	2,74	0.81
World Fleet Average Age	1,28	0.25	2,54	0.44
Number of new Bulkcarrier ships (built so far into the year)	0,99	-0.34	1,74	-0.42
Number of new Bulkcarrier ships (built so far into the year in DWT million)	0,97	-0.77	1,73	-0.67
Fleet Growth Percentage, (compared to previous year's Bulkcarrier world fleet)	0,93	-0.42	1,72	0.51
Bulkcarrier ships ordered to be built so far into the Year in Compensated gross tonnage	0,88	0.78	1,55	-0.65
Aluminum Price	0,85	0.62	1,24	0.77
Orderbook Percentage (compared to current Bulkcarrier world fleet stats)	0,78	-0.54	1,18	
Forecasted Future Brent Oil Price	0,71	0.55	1,17	-0.62
Forecasted Future Steel Rebar Price	0,67	0.71	1,15	-0.6
Bangladesh Steel Scrap Price Index	0,64	0.89	1,10	0.83
Bulkcarrier ships ordered to be built so far into the Year in Gross tonnage	0,63	-0.61	1,09	-0.78
Iron Ore Price	0,62	0.52	1,06	0.65

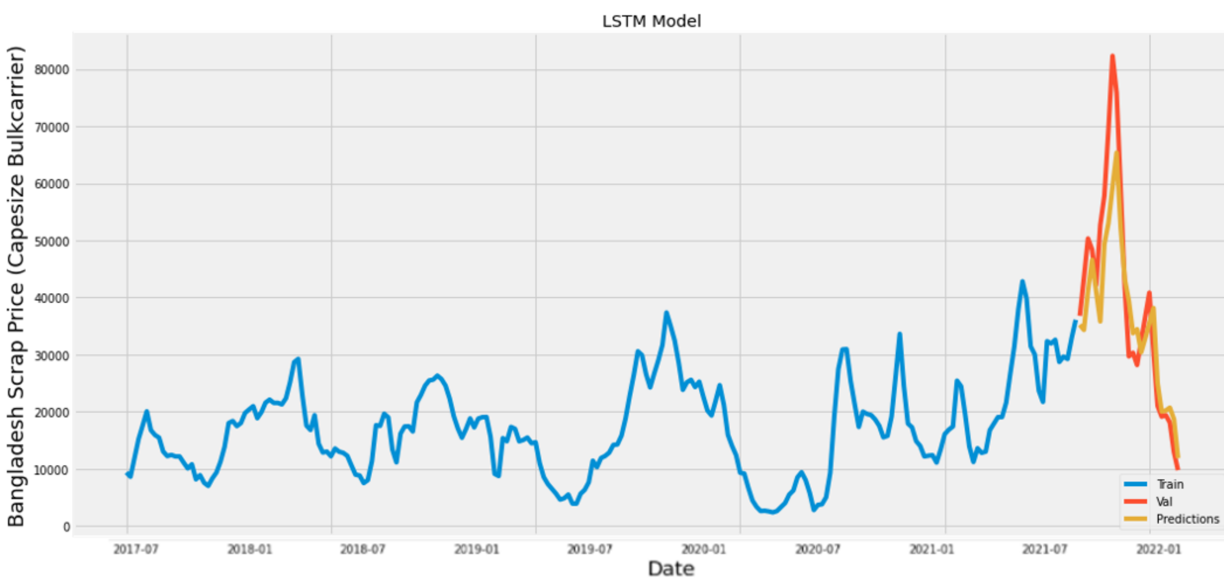
	Dependent Variable			
	Freight Rate		**Steel Scrap**	
Independent Variable	**Mutual Information Score**	**Pierson Correlation Coefficient**	**Mutual Information Score**	**Pierson Correlation Coefficient**
BITCOIN Price	0,60	0.62	1,04	-0.67
Number of Bulkcarrier ships ordered to be built so far into the Year	0,57	-0.54	0,97	0.84
Steel Rebar Price	0,57	0.71	0,96	0.74
Number of ships demolished so far into the year	0,43	0.86	0,92	0.84
Newcastle Coal Price	0,43	0.55	0,86	0.59
Bulkcarrier ships ordered to be built so far into the Year in DWT	0,40	-0.85	0,65	-0.28
Tons of Steel Scrapped so far into the year	0,33	0.89	0,41	0.65

Graphs.

Graph 3: Capesize Freight Rate 1-month ahead prediction interval RMSE=286.4, MAPE=13.6,MAE=3,167.3



Graph 4: Capesize Freight Rate 3-month ahead prediction interval RMSE=298.2, MAPE=15.8,MAE=3,461.9

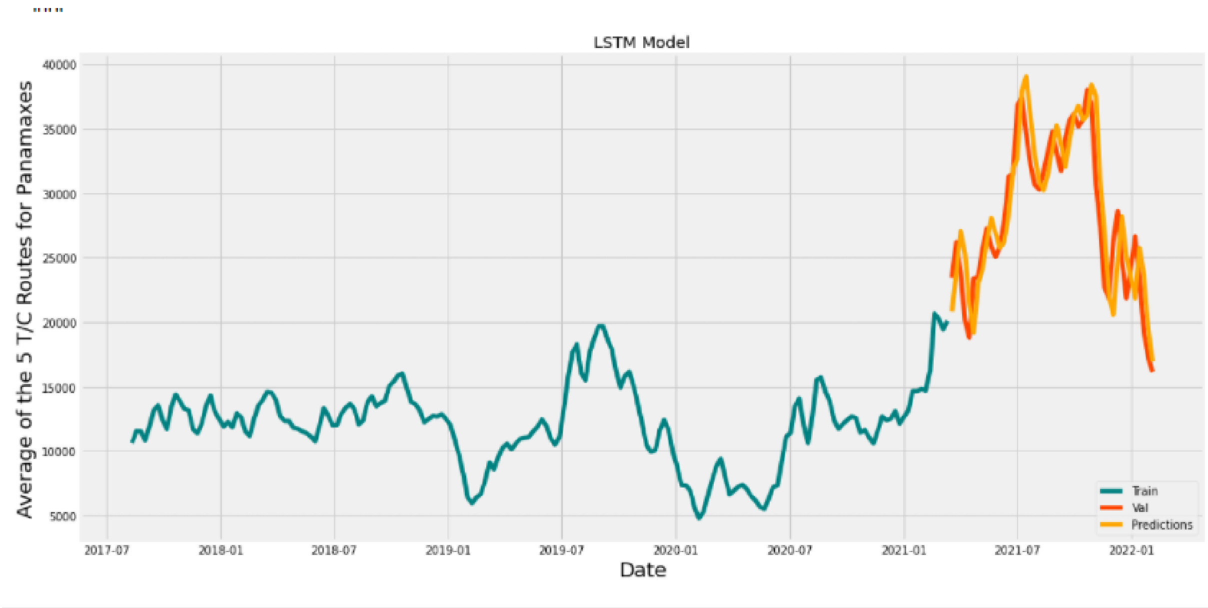


Graph 5: Supramax Freight Rate 1-month ahead prediction interval RMSE=406.15, MAPE=4.01,MAE=484.78.9

Graph 6: Supramax Freight Rate 3-month ahead prediction interval RMSE=623.15, MAPE=7.73,MAE=872.79

Graph 7: Panamax Freight Rate 1-month ahead prediction interval

RMSE=1,766.36, MAPE=5.83,MAE=1,995.37 74



Graph 8: Panamax Freight Rate 3-month ahead prediction interval

RMSE=2,332.2, MAPE=5.32,MAE=2,897.54

Graph 9: Steel Scrap Price 1-month ahead prediction interval

RMSE=9.90, MAPE=1.41,MAE=10

Graph 10: Steel Scrap Price 3-month ahead prediction interval RMSE=4.84, MAPE=2.23,MAE=14.7