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2030 Outlook for Global Cargo: ARIMA Predictions for Maritime Trade

2030 Küresel Yük Görünümü: Deniz Ticareti İçin ARIMA Tahminleri

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ANAHTAR KELİMELER

Denizcilik talebi

Yük hacmi

Deniz ticareti

ARIMA tahmini

Kuru yük

ÖZ

Deniz taşımacılığı sektörünün yüksek sermaye gereksinimleri göz önüne alındığında, karar verme sürecindeki hatalar önemli mali sonuçlara yol açabilir. Sonuç olarak, doğru gelecek tahminleri riski en aza indirmek için çok önemlidir. Bu çalışma, Kuru Yük, Ham Petrol ve Diğer Tanker yükleri olarak sınıflandırılan denizyolu yüklerinin 2030 yılına kadar olan görünümünü tahmin ederek sektör paydaşları ve politika yapıcılar için karar destek mekanizmaları sağlamayı amaçlamaktadır. Veri seti, 52 yıllık gözlemden oluşan 1970-2021 dönemini kapsamaktadır. Otoregresif Entegre Hareketli Ortalama (ARIMA) tahminlerimize göre, Kuru yük hacimlerinin 2021 yılına kıyasla 2030 yılına kadar %11,1 oranında artması beklenirken, Diğer Tanker yük hacimlerinin %1,2 oranında azalması ve Ham Petrol tanker hacimlerinin %10,7 oranında düşmesi öngörülmektedir. Çalışmanın tahminleri, gelişen yük ortamına ilişkin önemli bir anlayış sunmakta, küresel ticaret modellerindeki potansiyel değişimleri ve rekabet gücü ile verimliliği korumak için denizcilik sektöründe stratejik planlama ihtiyacını vurgulamaktadır. Bu bulgular, denizcilik sektörü katılımcılarının ve politika yapıcıların filo yönetimi, altyapı yatırımları ve değişen yük taleplerine uyum sağlamak için mevzuat düzenlemelerine ilişkin bilinçli kararlar almalarına yardımcı olacaktır.

KEYWORDS

Shipping demand

Cargo volume

Maritime trade

ARIMA forecast

Dry bulk

ABSTRACT

Given the high capital requirements of the maritime transportation sector, errors in decision-making can lead to significant financial consequences. As a result, accurate future projections are crucial for minimizing risk. This study aims to provide decision support mechanisms for industry stakeholders and policymakers by forecasting the outlook for seaborne cargoes—categorized as Dry, Crude Oil, and Other Tanker cargoes—through to 2030. The dataset covers the period from 1970 to 2021, consisting of 52 annual observations. Based on our autoregressive integrated moving average (ARIMA) estimates, Dry cargo volumes are projected to grow by 11.1% by 2030 compared to 2021, whereas Other Tanker cargo volumes are expected to decrease by 1.2%, and Crude Oil tanker volumes are anticipated to decline by 10.7%. The study's projections offer a crucial understanding of the evolving cargo landscape, highlighting potential shifts in global trade patterns and the need for strategic planning in the maritime industry to maintain competitiveness and efficiency. These findings will help maritime sector participants and policymakers make informed decisions regarding fleet management, infrastructure investments, and regulatory adjustments to adapt to shifting cargo demands.

1. Introduction

In the last decades, due to the increasing speed of globalization, the world economy is becoming increasingly dependent on freight transportation (Çakmak and Çalışkan,

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2024). While freight transportation activities increase the circulation of raw materials and finished products, they also support regional development economically. The increasing dependence of the world economy on freight transportation makes it imperative to improve freight transportation planning processes (Schank et al., 2008). Transport systems, which are of indisputable importance for today's world economy, are powerful systems open to change in terms of the form and amount of freight and passenger traffic at different time periods. The reasons for these changes are examined in the literature in three groups: economic, technical and organizational. And the correct assessment of these changes, the prediction of the supply-demand balance that determines the market price and the correct prediction of the future of the transport system are key elements of the planning and success of the system (Dragu et al., 2017).

In order to achieve well-functioning freight transportation systems, which are seen as an indispensable element of every successful economy, it is necessary to improve the demand for goods movement and the physical infrastructure in parallel and ensure that they act in harmony with each other. Freight transportation markets are markets with high time sensitivity (Regan et al., 2000). While the strengthening of this market, which can directly affect the strengthening of the global or regional economy, is among the important strategic goals of countries, the inadequacy of the physical infrastructure to meet the demand in question will, at best, lead to delays in freight transportation, will affect the country's economy in the opposite direction, and countries will be deprived of this value that creates an opportunity for economic strengthening.

Approximately 90% of international trade is carried out by maritime transport (Nuran, 2023). It is known that the main factors underlying the economic and political strength of many world countries with developed economies are the success and performance they have shown in the maritime field and the advantages they have gained from having a say in the world's seas (Germir, 2022). In this study, we aimed to estimate freight traffic up to 2030 using freight statistics published by UNCTAD. The research findings are crucial for both the maritime sector and policymakers, as the maritime industry is highly capital-intensive, requiring significant investments in infrastructure, superstructure, and ships. Mistakes in planning can lead to considerable inefficiencies and resource misallocation, making accurate forecasts essential for informed decision. Our findings hold significant importance for the maritime sector, providing benefits to transportation companies in three keyways. (i) With future load forecasting, shipping companies can optimize their fleets and plan capacity more effectively, minimizing the risk of both idle and insufficient capacity. (ii) Forecasts enable companies to make informed decisions regarding port infrastructure, storage facilities, and new ship orders, ensuring that resources are allocated efficiently. (iii) Demand forecasts help reduce financial risks by offering a clearer picture of future demand, allowing companies to better navigate uncertainties. Furthermore, the impact extends beyond transportation companies to other sectors, including shipbuilding yards, ship dismantling facilities, ports, provisioning companies, ship fuel suppliers, refineries, warehouses, alternative transportation modes, insurance providers, and mining companies. Given that these industries are closely linked to maritime transportation, accurate demand forecasting is crucial for their strategic planning and operational success. For policymakers, demand forecasts offer significant benefits in three main areas. (i) As policymakers are often responsible for planning and financing infrastructure investments, demand forecasts help assess how well a country's infrastructure can handle future traffic, thereby minimizing costly outcomes such as under- or over-investment. (ii) Changes in traffic volumes serve as indicators of economic trends, enabling policymakers to develop future commercial and economic policies. (iii) Shifts in freight traffic influence transportation costs due to factors such as economies of scale, service frequency, and delivery speed, making forecasts critical for sustaining commercial activities with sustainable transport costs.

Our ARIMA estimation results indicate that by 2030, the amount of dry cargo will increase by 11.1% compared to 2021, while the volume of other tanker cargo will decrease by 1.2%, and crude oil tanker volumes will decline by 10.7%. The decrease in crude oil transportation may be attributed to several factors, including the increasing transition to renewable energy sources (Khan and Shaheen, 2020; Yu et al., 2022), the growing adoption of electric vehicles (Unger, 2015; World Economic Forum, 2023), and the tightening of environmental regulations in the world and decarbonization policies in the maritime sector (Müller-Casseres et al. 2021). Yu et al. (2022: 2889) expressed that a strong conviction exists that progress in renewable energy sources eventually reduces the economy's dependence on crude oil and associated products. Khan and Shaheen (2020: 442) discovered a negative and significant connection between renewable energy use and crude oil import demand in nations such as China, India, and Japan. According to IRENA (2021: 75), the global economy's decarbonization would need the electrification of end-use industries, such as the road transport industry, which would reduce the amount of crude oil, and its derivatives traded. Climate policies lead to a decreased demand for global shipping as a result of diminished fossil fuel commerce. With the execution of a climate policy, a reduction in the market for coal, oil, gas, and chemicals may decrease global shipping activity by approximately 20% by 2050 and 25% by 2100 (Müller-Casseres et al. 2021: 10). Carbon pricing methods used in the transportation industry may elevate operational expenses for companies and projections indicate that shipping freight rates might rise by 10–30%, given the shipping sector's significant dependence on carbon-based fuels for optimal performance (UNEP FI, 2024: 10-11). If the commitments made to mitigate the effects of climate change are upheld, there will be a significant reduction in the demand for fossil fuels throughout the world for the duration of the long term

(Puyo et al., 2024: 2). Additionally, the shift of ships toward alternative, environmentally friendly fuels such as LNG, biofuel, and hydrogen—similar to the transition seen with electric vehicles—could also reduce the demand for oil-based fuels in shipping. According to Puyo et al. (2024), low and zero carbon hydrogen-based liquid fuels could substitute oil and they might acquire market share in oil-dependent aviation and shipping sectors. Improvements in energy efficiency further contribute to this decline in crude oil demand. The fact that other tanker cargoes did not decrease as much as crude oil can be interpreted as the rising demand for environmentally friendly cargoes, such as LNG, offsetting the decline in demand for petroleum products.

This study's novelty lies in its thorough and multifaceted approach to maritime cargo volume forecasting, which offers sector specific insights for optimal fleet management and resource allocation. The study also provides strategic planning insights for sustainable development in the maritime industry, with a focus on data-driven decision-making in infrastructure investments and policy formation for various maritime industry stakeholders.

The paper is structured as follows: Section 2 reviews the demand forecasting literature, particularly in the transportation industry. Section 3 identifies the data and methodology used in the study. The results are presented in Section 4, and finally, the findings and their implications are discussed in the last section.

2. Literature

In the current literature, there are many studies on demand forecasting in the transportation sector, conducted with different sample groups and different research methods. Tsekeris and Tsekeris (2011) compared the studies written in the field of demand forecasting in the transportation sector in terms of the methods they used. Lopes et al. (2014) analyzed the application of spatial statistics tools in the analysis of sustainable transportation planning and transportation demand. Okoro et al. (2016) provided a comprehensive perspective on the existing literature by examining the studies published on demand forecasting in the transportation sector, while Comi et al. (2012) studied on demand forecasting in urban freight transportation. Banerjee et al., (2020) investigated the subject of demand forecasting in the scheduled passenger transportation sector, and similarly, Wardman et al. (2007) studies on demand forecasting in the railway sector.

When examined within the scope of application areas, there are studies examining the subject of forecasting over the entire supply chain (Babai et al., 2022), in the railway sector (Profillidis and Botzoris, 2007; Tsai et al., 2009; Li et al. 2012; Milenković and Bojović, 2016), in the international airline sector (Faraway and Chatfield, 1998; Chen et al., 2009; Yao et al., 2014; Jungmittag, 2016; Ghomi and Forghani, 2016), in the maritime sector (Randers and Göluke, 2007; Dragu et al, 2017; Solak Fiskin, and Cerit, 2021; Ubaid et al. 2021; Wang et al, 2024), specifically in the shipbuilding sector (Gasparotti and Rusu, 2018; Wada et al.,2018; Wada et al., 2021; Han et al., 2024), demolition market (Kagkarakis et al. 2016), port sector (Tongzon, 1991; Jugović et al. 2011; Parola et al. 2020) and cruise line sector (Sun et al. 2011).

For the airline transportation, the studies included the variables such as monthly total airline passengers (Faraway and Chatfield, 1998), the number of people and freight transported, the distances traveled and aircraft operations in the main regions (Jungmittag, 2016), daily passenger data for business and economic class flights from an airline in Türkiye (Ghomi and Forghani, 2016). Additionally, daily train sales data (Tsai et al. 2009), monthly railway passenger volume (Li et al. 2012; Milenković et al. 2014) and average rail passenger travel distance, unit cost of transport by rail, car ownership index, number of busses working in interurban routes, unit cost of transport by bus etc. (Profillidis and Botzoris, 2007) were analyzed as variables in the forecasting studies for railway transportation mode. Forecasting studies related to tourism and passenger transportation industry were generally covered variables such as historical data of tourist/visitor arrivals in using time series, autoregressive moving average (ARMA), autoregressive integrated moving average (ARIMA) and seasonal autoregressive integrated moving average (SARIMA) forecasting (Ghalehkhondabi et al., 2019). Sun et al. (2011) taken into consideration of the booking histories cruises for a specific itinerary and cruise ship, and the details of the bookings included cruise's date of sail, week of departure, length of stay, type of cabin, and amount paid.

Solak Fiskin and Cerit (2021) reviewed and categorized forecasting studies for shipping industry and examined both theoretical and empirical investigations. They categorized the reviewed forecasting studies in shipping into following distinct themes; seaborne trade, average haul, ship demand, merchant fleet, ship productivity, freight rate, port/terminal traffic, and other shipping forecasts. According to the results of the study, while seaborne trade forecast studies mostly included export and import data, gross domestic product(GDP)/gross national product (GNP), trade volume, freight rate, commodity and distance as variables, the studies related to freight rate forecasting mainly covered new building, second-hand and demolition prices, freight index, freight rate, charter rates, oil price, oil production and fleet size/capacity variables. GDP/GNP, export and import data, new building prices and trade volume are the most frequently used variables in all covered studies. conversely, industrial production index, inflation rates, electric consumption, profits and expansion of building & construction are discovered as the least used variables in the studies.

ARIMA (Autoregressive Integrated Moving Average Model) is a modeling system that is widely used in literature in various fields such as GDP modeling (Muma and Karoki, 2022), energy consumption modeling (Aydın, 2014), food production estimation and modeling (Mishra et al., 2023), and estimation of population projections (Vanella et al., 2020). When evaluated specifically for the transportation sector, it has been determined that the ARIMA method is used in demand forecasting in regular passenger transportation (Banerjee et al., 2020), in air quality prediction inside transportation vehicles (Kadiyala and Kumar, 2014), in future traffic amount prediction (Liu et al., 2021), in studies on intelligent transportation systems (Han and Song, 2003; Kaffash et al, 2021), and in studies on tourism and passenger transportation sectors (Lim and McAleer, 2002; Ghalehkhondabi et al., 2019).

In the ARIMA method, the variables added to the model in order to achieve the purpose of the study are generally determined by the researcher in accordance with the nature of the study and supported by the literature. However, in the literature, the ARIMA model is generally used on highly correlated variables such as GDP, GNP, export, import (Khan and Khan, 2020), revenue (Kinney, 1978), etc. When examined specifically in the transportation sector, it was seen that in a study conducted for the purpose of estimating road transportation prices, the producer price index (PPI) for full truckload data obtained from the Bureau of Labor Statistics (BLS) and the average monthly price data obtained from a website serving as an online freight board for road transportation were used (Miller, 2019), and in a study aimed at estimating the gasoline consumption amounts of the transportation system in a certain region, the gasoline consumption data of the previous period in the same region were included in the model (Waheed Bhutto, et al., 2017).

When the studies conducted using the ARIMA method on the maritime sector are examined, it is observed that in the study aiming at effective maritime accident estimation, variables such as "*number of maritime accidents, capsizing, collision, contact, fire/explosion, hull failure, stranding/grounding, adverse weather conditions*" (Wang et al., 2023) were added to the model, while in a study conducted to measure the impact of the economic crisis on maritime trade, variables such as "*number of passenger ships, number of passengers, number of passengers embarked in Greek ships, number of passengers embarked and disembarked, GDP, unemployment rate, employment, oil price, active population*" (Aivazidou and Politis, 2017) were included. In addition, it is possible to come across univariate models in the form of time series for a specific purpose in the literature; examples include the study where recorded data of cargo/container throughput is used to estimate cargo volume at ports (Shu, et al., 2014; Bal and Çalışır, 2018), where the container handling volume of a given country is used to estimate container volume in that country within a certain time period, or where weekly data from China Containerized Freight Index (CCFI) and Shanghai Containerized Freight Index (SCFI) are used to estimate container freight rates on a given route (Munim and Schramm, 2017), or Baltic Dry Index (Şahan et al., 2018).

A review of the literature reveals that most studies on the demand side of maritime transportation tend to focus on specific aspects such as container volumes, freight rates, passenger numbers, and ship counts. However, forecasting total cargo volumes in the context of global cargo traffic offers critical insights into the future of freight rates by accounting for supply-demand dynamics. Moreover, since container shipping involves final products, the demand for cargoes like dry bulk, energy, and general goods significantly influences container demand. In this regard, forecasting all cargo types globally, using the United Nations Conference on Trade and Development (UNCTAD) classification, provides a more comprehensive analysis of market trends. The originality of our study lies in this holistic approach to global cargo forecast, which enhances the understanding of interconnected markets. Our findings are highly beneficial for transportation companies, enabling them to optimize fleet management, plan port infrastructure and new ship orders, and mitigate financial risks by forecasting future cargo demand. These forecasts also benefit related sectors such as shipbuilding, demolition, ports, fuel suppliers, and insurance, all of which rely on maritime transport for strategic planning. For policymakers, demand forecasts assist in infrastructure investment planning, provide insights into economic trends, and help manage transportation costs, ensuring sustainable commercial activity and economic policy development.

3. Data and Methodology

We collected data on seaborne shipments of dry cargo, crude oil, and other tanker cargoes, published by UNCTAD (2024), measured in millions of metric tons. The dataset covers the period from 1970 to 2021, consisting of 52 annual observations. It represents cargo traffic through global seaports, excluding cabotage and transshipment cargoes. Dry cargo refers to cargo such as dry bulks (e.g., coal, ores, grains), pallets, bags, crates, and containers. 'Other tanker' refers to tanker trade excluding crude oil and includes refined petroleum products, gas, and chemicals.

When examining the annual averages, Dry Cargo emerges as the most transported category, with an average of 3.7 billion metric tons per year. The highest volume recorded was 8 billion metric tons in 2021. Crude Oil Cargo ranks second, averaging 1.5 billion metric tons annually, followed by Other Tanker Cargo, which averages 6.4 million metric tons.

An analysis of the descriptive statistics for annual average growth rates reveals that Dry Cargo experienced the highest growth rate, averaging 4.7% per year. This is followed by Other Tanker Cargo at 3.3%, and Crude Oil Cargo at 0.6%. In terms of maximum annual growth rates, Other Tanker Cargo saw the largest increase, surging by 48.2% between 2005 and 2006. Dry Cargo recorded a 24.4% growth between 1997 and 1998, while Crude Oil Cargo experienced a 13.6% growth from 1972 to 1973. The sharp increase in Other Tanker Cargo between 2005 and 2006 is thought to be due to the hurricanes that devastated the Gulf of Mexico and the southern states of the United States in late 2004. Due to the destruction of a significant portion of U.S. refinery capacity and oil and gas production at the end of the Atlantic hurricane season, especially after the second half of 2005, the demand for both gasoline and other tanker cargoes was high and their inventories were quite low, which rapidly increased the demand for refined petroleum product imports during the period in question (Danish Ship Finance, 2006). When the Dry Cargo increase between 1997 and 1998 is examined, it is observed that the increase in economic growth in Western Europe and the USA in 1997 increased the world dry cargo demand, and that the world dry cargo demand entered a decreasing trend due to the emergence of the Asian financial crisis in early 1998 (UNCTAD, 1998). When the increase in Crude Oil Cargo observed between 1972-1973 is examined, it is observed that the US made changes in its oil import policies as a result of the increase in demand for oil in Western Europe, Japan and especially the USA, which switched to an accelerated economic growth program in the given period (UNCTAD, 1973).

The periods with the greatest shrinkage were observed for Dry Cargo, with a 5.8% decline from 2008 to 2009, for Crude Oil, with a 15.9% drop from 1981 to 1982, and for Other Tanker Cargo, with a 17.9% decrease from 1974 to 1975. The contraction in Dry Cargo can be interpreted as a natural consequence of the global financial crisis of 2008, which affected global demand. This financial crisis caused the sector to remain stagnant for a long time, even. In particular, the Baltic Dry Index (BDI), representing the dry bulk shipping sector, fell by approximately 94% in just two quarters and fell to 663 points on December 5, 2008 (Park et al., 2023). So, the contraction in Dry Cargo can be interpreted as a natural consequence of the financial crisis, which affected global demand. When it comes to the Crude Oil, although energy saving practices, discovery of alternative energy substitutes, production opportunities closer to consumer countries and the current world recession are among the reasons for the decline, it is assumed that a few pipelines that started operating in 1981-1982 also affected the decline (UNCTAD, 1982). When we examine the decline in the Other Tanker Cargo category, it is seen that the cheap oil concept, which was believed to have an infinite supply and always low price until 1973, the very low production costs in the Middle East, new oil production especially in the British and Norwegian sectors in the North Sea, and the belief in an infinite supply increased. However, in the fall of 1973, this understanding suddenly ended with the Yom Kippur War between Israel and the Arab world, and Arab oil producers realized that they had a powerful weapon in their hands. During the 1973 Arab-Israeli War, the Arab members of the Organization of the Petroleum Exporting Countries (OPEC) imposed an embargo on the US in retaliation for the US's decision to aid the Israeli army, and this significantly affected the world oil supply (Tenold, 2019). Therefore, it is evaluated that the decline in question refers to the 1975 Oil Crisis, which also has an important place in history.

An examination of the skewness values reveals that Dry and Other Tanker cargoes have positive skewness, while Crude Oil cargo has negative skewness. This indicates that for Crude cargo, extreme negative growth values have a greater impact than positive ones, leading to sudden declines during the period analyzed. Conversely, for Dry and Other Tanker cargoes, extreme positive growth values occur more frequently than negative ones, reflecting the tendency for these categories to experience sharp increases.

Table 1. Descriptive Statistics of the Variables

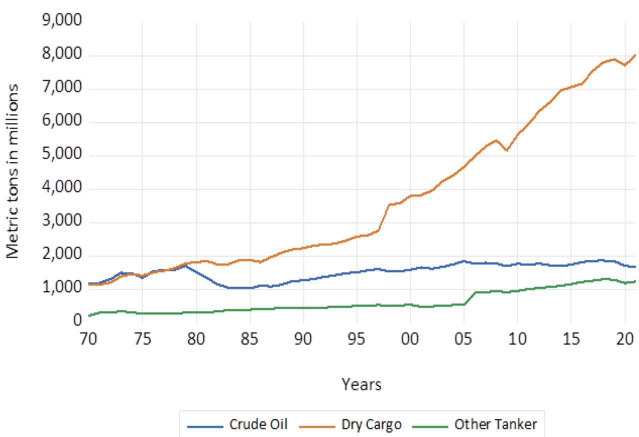
	DRY	CRUDE	O. TANKER	DLOG DRY	DLOG CRUDE	DLOG O. TANKER
Mean	3680.231	1539.000	636.7692	0.037860	0.006715	0.032970
Median	2616.000	1594.500	509.0000	0.038837	0.019231	0.027196
Maximum	8033.000	1881.000	1320.000	0.243855	0.136366	0.482098
Minimum	1162.000	1049.000	233.0000	-0.057974	-0.159419	-0.179341
Std. Dev.	2216.703	246.9175	338.4659	0.046421	0.058116	0.090387
Skewness	0.667280	-0.522720	0.815491	1.483570	-0.539942	2.690964
Kurtosis	2.025287	2.074033	2.154921	9.526269	3.839383	15.29807
Jarque-Bera	5.917420	4.225778	7.310898	109.2167	3.975268	382.9411
Probability	0.051886	0.120888	0.025850	0.000000	0.137019	0.000000
Observations	52	52	52	51	51	51

Source: UNCTAD (2024)

Figure 1 presents the trends of the variables considered in the study between 1970 and 2021. The observed patterns align with the insights derived from the descriptive statistics. In the 1970s, Crude Oil and Dry Cargo volumes were transported in nearly equal amounts. However, by 2021, a significant divergence is evident, with Dry Cargo being transported approximately 4.72 times more than Crude Oil. Additionally, the gap between Crude Oil and Other Tanker cargoes has narrowed over time. In 1970, Crude Oil was transported 5.18 times more than Other Tanker cargoes, but by 2021, this ratio had reduced to 1.35 times. These observations highlight the declining importance of Crude Oil in global transportation, reflecting its shrinking share in overall cargo volumes over time.

As observed, while total demand for maritime transportation has increased over time, the demand for different cargo types varies significantly. In this context, making accurate forecasts by cargo type is crucial for industry stakeholders, policymakers, and investors. To address this need, we have decided to use the Autoregressive Integrated Moving Average (ARIMA) methodology to estimate the future volumes of Dry, Crude Oil, and Other Tanker cargoes through 2030. The method is usually associated with Box and Jenkins (1976).

Figure 1. Raw Data



Source: UNCTAD (2024)

The Box-Jenkins method allows the dependent variable Y_t to be explained by its past or lagged values, and by the current and lagged values of the error term u_t. In the ARIMA model, which follows the Box-Jenkins methodology, it is assumed that the series is stationary. If the series is not stationary, it can be made stationary by differencing it. When a series is already stationary, the ARIMA (p, d, q) model reduces to an ARMA (p, q) model (Aljandali and Tatahi, 2018: 111). The simple ARMA (p, q) model can be represented by the following equation:

$$Y_t = \beta_0 + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \cdots + \beta_p Y_{t-p} + C_1 u_{t-1} + C_2 u_{t-2} + \cdots + C_q u_{t-q} + u_t$$

where:

- Y_t is the dependent variable at time t
- β_i are the autoregressive (AR) parameters
- C_i are the moving average (MA) parameters
- v_t is the error term at time t

We used the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) (Kwiatkowski et al., 1992) stationarity test to determine the d value by assessing whether the variables are stationary. The null hypothesis of the KPSS test assumes that the series is stationary, and for stationarity to be confirmed, the null hypothesis must be accepted. The KPSS test stands out as a more robust option compared to other unit root tests, particularly when a deterministic trend is present in the series. ARIMA models are typically applied to stationary series without a trend (Shmueli and Polak, 2024: 157). However, given that our data is observed annually, and our goal is to make forecasts, we have chosen not to separate the trend from trend stationary series.

4. Results

In the results section, we first present the identification of the ARIMA (p, d, q) model, followed by the forecasting process using the selected model. The analyses were conducted using EViews econometric software.

4.1. Determination of the ARIMA Models

In the ARIMA methodology, the value of d is determined by testing the stationarity of the variables. To assess this, the KPSS stationarity test was applied to all variables, and the results are presented in Table 2. The findings indicate that the null hypothesis of stationarity is accepted at the level for all three variables at 10% significance level, meaning the d value is 0. The Dry Cargo and Other Tanker cargo series are trend stationary, indicating that these series fluctuate around a deterministic trend. In contrast, the Crude Oil series is both intercept and trend stationary, suggesting that it tends to revert to the mean over time. The stationarity of Crude Oil series at the level indicates that it tends to revert to the mean, fluctuating around a certain average in a statistical sense. In contrast, Dry Cargo and Other Tanker Cargo series exhibit trend stationarity, moving around a certain trend, which, as seen in the graphs, follows an upward trajectory. The stationarity of all variables suggests that the effects of shocks are temporary, and in the long run, they revert to their respective tendencies.

Table 2. KPSS Stationarity Test Results

	Level		First Difference		
	Intercept	**Intercept & Trend**	**Intercept**	**Intercept & Trend**	**Conclusion**
Dry Cargo	0.966	***0.155	*0.095	*0.097	I (0)
Crude Oil	***0.615	*0.096	*0.071	*0.067	I (0)
Other Tanker	0.922	**0.143	*0.048	*0.051	I (0)

Note: CVs are 0.739 for ***1%, 0.463 for **5%, 0.347 for *10% at Intercept, 0.216 for ***1%, 0.146 for **5%, and 0.119 for *10% at Trend and Intercept. Barlett kernel spectral estimation method is used. Bandwidth is selected automatically by using Newey-West.

After determining the d value in the model, the automatic ARIMA forecasting function in EViews software was used to identify the AR and MA values, with the maximum set at AR = 12 and MA = 12. The software was also permitted to apply logarithmic transformations to the variables when necessary. The AR and MA values that minimized the

Akaike Information Criterion (AIC), with a preference for logarithmic transformations, are presented in Table 3. As a result, the ARIMA (2, 0, 1) model for Dry Cargo, ARIMA (1, 0, 3) for Crude Oil, and ARIMA (2, 0, 1) for Other Tanker were identified as the optimal models. Since all series are stationary, their degrees of integration are set to 0. The identified models were then estimated using the Least Squares method.

Table 3. ARIMA Model Specifications

	Dry Cargo	Crude Oil	Other Tanker
AR	2	1	2
MA	1	3	1
Integration	0	0	0
AIC Value	-2.9575	2.8628	-1.6737

4.2. Forecast Results

Since the objective of this research is focused on forecasting rather than interpreting the model's coefficients, the individual significance of the AR and MA variables has been disregarded. Instead, insignificant variables suggested by EViews, which enhance the model's goodness of fit and prediction accuracy, have been retained. To ensure model validity, several checks were performed: the F-test to assess the overall significance of the model, confirmation that the AR and MA roots are inverted, and verification that no autocorrelation is present.

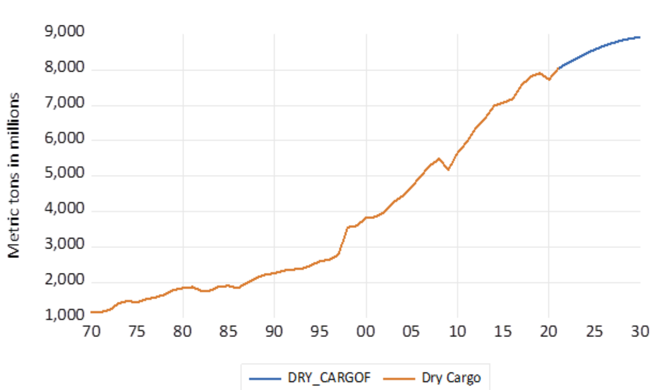
The results of the ARIMA (2, 0, 1) model estimated for Dry Cargo are presented in Table 4. The F-test confirms that the model is significant overall, the AR and MA roots are inverted, and the Ljung-Box test, applied with 7 lags, indicates no presence of autocorrelation.

Table 4. Estimation of the Dry Cargo Model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	8.005059	0.322602	24.81405	0.0000
AR(1)	1.996610	0.024575	81.24635	0.0000
AR(2)	-0.998285	0.022666	-44.04259	0.0000
MA(1)	-1.000000	2949.851	-0.000339	0.9997
SIGMASQ	0.002113	0.143490	0.014728	0.9883
R-squared	0.994203		**Mean dependent var**	8.030523
Adjusted R-squared	0.993710		**S.D. dependent var**	0.609670
S.E. of regression	0.048354		**Akaike info criterion**	-2.957555
Sum squared resid	0.109893		**Schwarz criterion**	-2.769936
Log likelihood	81.89644		**Hannan-Quinn criter.**	-2.885627
F-statistic	2015.126		**Durbin-Watson stat**	1.950244
Prob(F-statistic)	0.000000			
Inverted AR Roots	1.00+.04i	1.00-.04i		
Inverted MA Roots	1.00			

The results for Dry Cargo volume forecast from 2022 to 2030 are presented in Figure 3. Demand, which contracted slightly due to the pandemic in 2020, resumes the upward trend that began in 2021, reaching 8,927 million metric tons in 2030, up from 8,033 million metric tons, though with a decreasing growth rate. This situation indicates that demand will continue its upward trend, albeit at a slowing rate.

Figure 3. Forecast of Dry Cargo



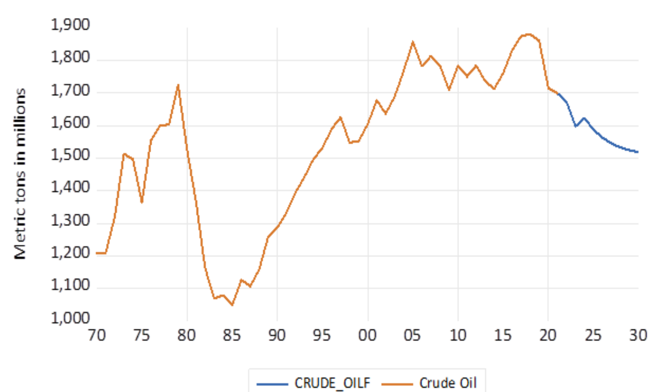
The results of the ARIMA (1, 0, 3) model estimated for Crude Oil cargo are presented in Table 4. The F-test confirms that the model is significant overall, and the AR and MA roots are inverted. The Ljung-Box test, applied with 7 lags, detects autocorrelation up to 2 lags at the 99% significance level, after which autocorrelation disappears. Additionally, the results of the autocorrelation test were disregarded because the residuals of the model passed the normality test, indicating a normal distribution.

Table 5. Estimation of the Oil Cargo Model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	7.314860	0.065116	112.3361	0.0000
AR(1)	0.714926	0.119299	5.992711	0.0000
MA(1)	0.615054	351.4773	0.001750	0.9986
MA(2)	0.512758	236.6852	0.002166	0.9983
MA(3)	0.897694	946.4744	0.000948	0.9992
SIGMASQ	0.002285	0.388944	0.005876	0.9953
R-squared	0.920214	**Mean dependent var**		7.325172
Adjusted R-squared	0.911541	**S.D. dependent var**		0.170891
S.E. of regression	0.050826	**Akaike info criterion**		-2.862907
Sum squared resid	0.118833	**Schwarz criterion**		-2.637763
Log likelihood	80.43557	**Hannan-Quinn criter.**		-2.776592
F-statistic	106.1080	**Durbin-Watson stat**		1.916854
Prob(F-statistic)	0.000000			
Inverted AR Roots	.71			
Inverted MA Roots	.19-.93i	.19+.93i	-1.00	

The forecast results for Crude Oil Cargo for the period from 2022 to 2030 are presented in Figure 4. Transportation, which has not experienced an upward trend like other cargoes and has remained relatively stable in incoming cargo, is projected to continue the downward trend that began after 2018, reaching 1,518 million metric tons by 2030. The rate of decline, which initially started sharply, is expected to follow a slightly more gradual course, as significantly reducing the demand for oil is a process that can take decades and cannot be accomplished in a short period.

Figure 4. Forecast of Crude Oil Cargo



The results of the ARIMA (2, 0, 1) model estimated for Other Tanker Cargo are provided in Table 4. The F-test verifies that the model is statistically significant overall, the AR and MA roots are properly inverted, and the Ljung-Box test with 7 lags confirms that there is no evidence of autocorrelation.

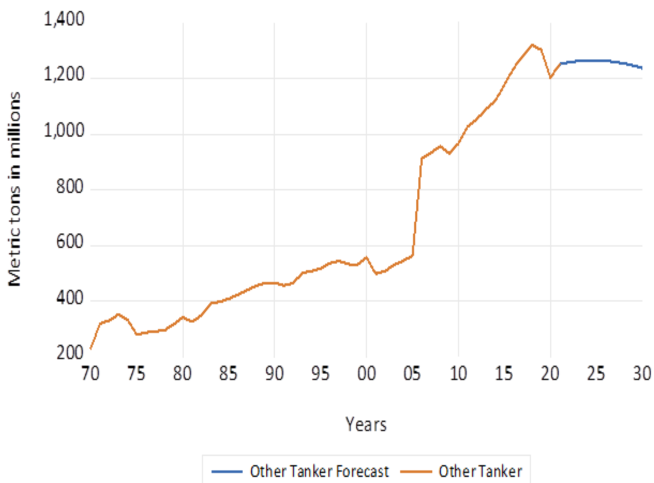
Table 6. Estimation of the Other Tanker Model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	6.263814	0.543424	11.52658	0.0000
AR(1)	1.988725	0.066608	29.85720	0.0000
AR(2)	-0.990503	0.065095	-15.21622	0.0000
MA(1)	-0.999834	40.58679	-0.024634	0.9805
SIGMASQ	0.008117	0.369018	0.021996	0.9825
R-squared	0.967405	**Mean dependent var**		6.327725
Adjusted R-squared	0.964631	**S.D. dependent var**		0.503893
S.E. of regression	0.094765	**Akaike info criterion**		-1.673740
Sum squared resid	0.422082	**Schwarz criterion**		-1.486120
Log likelihood	48.51724	**Hannan-Quinn criter.**		-1.601811
F-statistic	348.7352	**Durbin-Watson stat**		2.054256
Prob(F-statistic)	0.000000			
Inverted AR Roots	.99+.04i	.99-.04i		
Inverted MA Roots	1.00			

The forecast result for Other Tanker Cargo from 2022 to 2030 is presented in Figure 5. It is estimated that this cargo will also begin a downward trend following a period of smooth growth. The transportation volume, which was

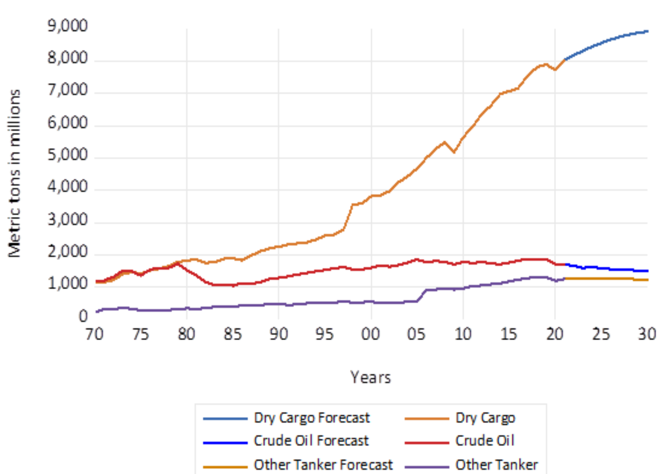
1,251 million metric tons in 2021, is projected to decrease to 1,237 million metric tons by the 2030s.

Figure 5. Forecast of Other Tanker Cargo



To provide a comprehensive view of the maritime market, the forecast graphs for all three cargo types have been combined and are presented in Figure 6. As shown, while Crude Oil and Other Tanker cargo types remain close to each other, the Dry Cargo type diverges, with the gap between them widening over time.

Figure 6. Forecast of All Three Cargo Types



After developing the models and generating the forecasts, the estimates for 2030 and their percentage changes compared to 2021 are presented in Table 4. The results indicate that Dry Cargo is projected to grow by 11.1%, reaching 8.9 billion metric tons. In contrast, Crude Oil Cargo is expected to decline by 10.7%, reaching 1.5 billion metric tons, while Other Tanker Cargo is forecasted to decrease by 1.2%, reaching 1.2 billion metric tons. This indicates that for Dry Cargo, the demand will rise to the point where a 1 additional ship will be required for every existing 10 ships in operation. In contrast, for Crude Oil, there will be no need for 1 out of every 10 current ships, reflecting a significant decline in demand. Meanwhile, the demand for Other Tankers is expected to remain relatively stable, showing only a slight decrease. This is because Other Tanker Cargoes consist largely of processed petroleum products, meaning that a decrease in demand for crude oil will naturally lead to a decline in such cargoes. However, the increasing demand for LNG, biofuels, and other types of tanker fuels helps offset the severity of the negative impact from the reduction in oil demand. Thus, Other Tanker Cargoes follow a relatively more stable course.

Table 4. Estimated Changes of Demands in 2030

	2021 (Current)	2030 (Estimation)	% (Change)
Dry Cargo	8.033	8.927	11.1%
Crude Cargo	1.700	1.518	-10.7%
Other Tanker Cargo	1.252	1.238	-1.2%

5. Conclusion

Our findings include important policy recommendations for various industry stakeholders. For shipowners, since the demand for Dry Cargo is expected to increase by approximately 11.1% by 2030, shipowners in this sector should invest in expanding their fleets and upgrading their existing vessels. A competitive advantage can be achieved through economies of scale by opting for larger ships. On the other hand, with the anticipated 10.7% decrease in Crude Oil Cargo demand, shipowners in this sector should diversify their fleets to carry other types of cargo. For instance, given the expected growth in Dry Cargo demand, they could transition into that sector or invest in more flexible ship types to accommodate a wider range of cargoes. In addition, since the decline in demand for oil is largely driven by environmental regulations aimed at reducing environmental damage, shipowners across all cargo groups should transition to environmentally friendly, clean energy fuel types. In 2021, the European Commission (EC) launched its 'Fit for 55' legislation package, aiming to decrease the European Union's (EU) greenhouse gas (GHG) emissions by 55% by 2030. The European Commission recommends the inclusion of shipping in the European Emission Trading System (EU ETS). Notwithstanding advancements in recent years, the marine industry remains mostly dependent on fossil fuels, representing a substantial source of greenhouse gas emissions and other detrimental pollutants. The objective of the FuelEU maritime effort is to diminish the greenhouse gas intensity of energy used on ships by up to 80% by 2050. The revised regulations encourage the use of renewable and low-carbon fuels in maritime transport (European Council, 2024). Since January 2024, EU ETS has been expanded to include CO2 emissions from any big ships (with a gross tonnage of 5,000 or more) that visit EU ports, irrespective of the flag which they fly (European Commission, 2024). As regulations tighten, the pressure on shipowners still using fossil fuels will increase, making it essential to adopt cleaner alternatives to remain compliant and competitive.

In addition to all these results, another important element that should not be ignored is that when the results obtained in the study and presented in Fig. 3, 4 and 5 are examined, there have been periodic fluctuations in demand amounts for all cargo types throughout history. When the reasons for these fluctuations are examined retrospectively, various reasons such as natural disasters (hurricanes), global financial crises, policy changes of the world's major powers, the discovery of alternative energy sources and wars emerge. It will always be possible for such difficult-to-predict risks, also called geopolitical risks in literature, to affect the estimated cargo demands on a local or global scale in the future as they did in the past. When monitoring the crude oil transportation process, the effect of the Iranian Revolution in 1979 is clearly evident. During this period, oil prices surged from $11 to $40, leading to a significant decrease in demand for oil. As a result, maritime crude oil transportation declined, and many tanker ships were laid up (Stopford, 2009:129).

For cargo owners, changes in demand affect future available capacity, making it essential to develop proactive policies. Dry Cargo owners can secure transportation capacity by entering into long-term contracts to avoid potential capacity shortages due to the anticipated increase in demand. Crude Oil cargo owners, on the other hand, should optimize their logistics and storage facilities to minimize costs during potential future downturns, thus avoiding the financial risks associated with excess or underutilized infrastructure.

For shipyards, the differentiation of demand for ship types is crucial in the policy development stages. As environmental regulations become increasingly stricter, shipyards should prioritize green shipbuilding and specialize in the production of alternative fuel-powered and energy-efficient ships. Additionally, with both expansion and replacement demand expected to be high due to the growing demand for Dry Cargo, shipyards should adjust their capacities to accommodate this type of vessel. Furthermore, they can explore expanding ship conversion options, enabling excess tankers to be repurposed for use in different sectors.

In addition, changes in demand have significant implications for economies that are heavily reliant on a particular type of cargo. Countries whose economies depend heavily on oil exports should invest in diversifying their export portfolios, as they are likely to be negatively impacted by declining oil demand and prices. To ensure a smooth economic transition, these countries should focus on increasing the share of other goods and services in their economies. Additionally, they could prioritize exporting higher value-added petroleum products by investing in refining capacity, rather than relying solely on crude oil exports. Similarly, countries whose economies rely on Dry Bulk products can mitigate the risk of being unable to meet future demand by increasing investments in infrastructure and equipment. These investments will enable them to handle the expected rise in demand more efficiently and ensure that they can capitalize on the growing market opportunities.

In our study, we utilized univariate ARIMA models to estimate the transportation rates of three different cargo types until 2030, based on the classification provided by UNCTAD. Our primary limitation lies in the fact that the heterogeneous diversity of cargo types is grouped into only three main classifications. This simplification stems from challenges related to limited data access, which restricted our ability to incorporate a more granular categorization of the various cargoes. As a result, some nuances in load diversity may not be fully captured in our analysis. For future research, estimates for sub-groups of cargo, such as dry bulk, container, LPG, and LNG, could provide more sector-specific insights. The ARIMA method we employed estimates future values by relying solely on past data from a single variable, which inherently disregards the potential influences of other factors that may affect the variable under estimation. This limitation highlights the importance of exploring alternative methods that account for the effects of multiple variables, providing a more comprehensive understanding of the relationships under investigation. Future studies would benefit from incorporating such multivariate approaches to offer deeper insights. Additionally, incorporating different methods that account for the effects of other variables, such as ship supply, oil prices, inflation, exchange rates, interest rates, commodity prices, and freight rates, could lead to more accurate and comprehensive forecasts.

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