Available online at http://dx.doi.org/10.29228/javs.80361
ISSN: 2149-8598

Research Article

The Future of Maritime Crude Oil and Dry Cargo Transportation: 2030 Forecast Using the SVR Method

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Abstract

This study aims to analyze past trends in maritime transportation of crude oil and dry cargo and provide future projections. The research employs the Support Vector Regression (SVR) method. Data from the 1970–2021 period, sourced from UNCTAD, has been utilized to evaluate the future dynamics of maritime transport. The findings indicate that dry cargo transportation has grown steadily, driven by global trade expansion, industrial growth, and infrastructure development. The volume of dry cargo transported is expected to reach 9.695 billion tons by 2030. This growth underscores the need for increased infrastructure investments within the sector. In contrast, crude oil transportation has exhibited a stagnant trajectory due to transformations in energy markets and the widespread adoption of renewable energy sources. The transported volume of crude oil is projected to continue its downward trend through 2030. This trend highlights the necessity for flexible and innovative strategies in energy transportation. The study contributes to the development of sectoral strategies aligned with sustainability and operational efficiency goals in the maritime industry.

Keywords: Maritime Transportation, Crude Oil Transportation, Dry Cargo Transportation, Support Vector Regression

For Citation: Filiz, T. (2025). The Future of Maritime Crude Oil and Dry Cargo Transportation: 2030 Forecast Using the SVR Method. *Journal of Academic Value Studies, 11*(1), 22-33. http://dx.doi.org/10.29228/javs.80361

Received: 16.01.2025 Accepted: 23.03.2025 This article was checked by ***intihal.net***

1. Introduction

Maritime transportation is a cornerstone of global trade, playing a critical role in the growth and sustainability of the global economy. By facilitating cost-effective international trade, it accelerates the flow of goods between nations (Kosowska-Stamirowska, 2020). Additionally, this mode of transport handles approximately 80% of global trade volume, offering significant advantages over other modes in terms of energy consumption and environmental impact (Golubkova, 2023). The strong link between economic growth and maritime transportation highlights the importance of aligning economic structures with transportation policies. In the European Union, investments in maritime transport have been shown to drive economic growth (Adam et al., 2021), emphasizing the critical importance of maritime strategies for national economies (Dihayco-Garciano & Garciano, 2023).

Maritime transport facilitates the secure and efficient movement of diverse cargo types. Crude oil and dry cargo, in particular, stand out as two core segments of the industry. Crude oil, a key component of global energy markets, is carried across continents by enormous tankers, guaranteeing worldwide supply and demand balances. According to Mert & Çetinyokuş (2020) and Jia (2018), maritime transportation accounts for nearly 40% of global crude oil output. Vidmar & Perkovič (2018), on the other hand, state that approximately 50-60% of global crude oil production is transported via marine routes, reflecting its role in international trade. However, this process confronts problems, such as crude oil price volatility, which has a direct influence on freight costs and operational planning (Siddiqui and Verma, 2015). Furthermore, the environmental impacts of crude oil transportation, notably greenhouse gas emissions, necessitate the use of sustainable practices and optimization technology (Greene et al., 2020).

Dry cargo, encompassing essential commodities such as grain, coal, and ore, constitutes an important component of industrial and agricultural supply chains worldwide. The bulk transport of these goods ensures food security, supports manufacturing operations, and sustains global trade flows. For example, dry cargo shipping facilitates the continuous movement of raw materials critical for industry and agriculture, reducing operational costs and enhancing supply chain resilience through effective planning and logistical optimization (Khaslavskaya & Roso, 2019). As global demand for raw materials continues to rise, the efficient management of dry cargo volumes becomes increasingly important to prevent bottlenecks and accommodate future industrial needs (Jiang et al., 2024).

The maritime transportation sector is subject to significant annual fluctuations in cargo volumes due to factors such as global economic shifts and sudden changes in supply-demand dynamics. In crude oil transport, market volatility and geopolitical events often result in uncertainties in annual tonnages (Sharma & Yadav, 2020). Dry cargo transport, on the other hand, is directly influenced by changes in agricultural production, industrial demand, and logistics infrastructure (Zhu & Hsieh, 2024).

In the literature on crude oil transportation forecasting, the study by Özispa et al. (2024) provides a comprehensive analysis of the sector. This research projects a 10.7% decline in crude oil tanker volumes by 2030, highlighting potential shifts in global trade patterns and discussing their implications for fleet management, infrastructure investments, and regulatory policies. Other studies, however, primarily focus on price forecasting. Bollapragada et al. (2021) and Li et al. (2022) proposed theoretical and AI-based models to address the nonlinear nature of crude oil prices. Similarly, Moiseev (2021) and Guo et al. (2023) employed adaptive and machine learning methods for price prediction. However, no study utilizing the SVR method to forecast future crude oil volumes has been identified.

In the forecasting literature on dry bulk shipping, the study by Özispa et al. (2024) projects an 11.1% growth in dry cargo volumes by 2030, highlighting the potential for future expansion in this segment. Goulielmos (2018) emphasized the importance of anticipating market cycles and utilized the "Radial Basis Functions" method for long-term predictions. Katris & Kavussanos (2021) evaluated short-term forecasting accuracy for the Baltic Dry Index (BDI) using ARIMA, FARIMA, and machine learning methods. Inglada-Pérez & Coto-Millán (2021) analysed the nonlinear dynamics and chaotic structures within the BDI, demonstrating the explanatory power of GARCH and EGARCH models in addressing market volatility. However, no studies employing the SVR method for volume forecasting in the dry cargo sector have been identified.

SVR demonstrates strong capabilities in handling nonlinear and complex data sets, making it especially effective in volatile fields such as energy markets and maritime transportation. By improving the accuracy of market forecasts, SVR serves as a crucial tool for guiding investment decisions and managing risks.

Studies in the literature consistently underscore the strength of SVR as a predictive tool in handling complex and nonlinear data. Han et al. (2014) demonstrated the versatility of SVR by combining it with wave transformation techniques to forecast the BDI. This approach not only improved short-term forecasting but also underscored SVR's robustness in managing price risks within volatile dry bulk shipping markets. Similarly, Bao et al. (2016) highlighted the method's inherent capacity to model market patterns effectively by integrating macroeconomic indicators into an SVR framework for predicting BDI trends.

In the domain of crude oil price forecasting, SVR has proven to be particularly effective due to its ability to process nonlinear and intricate datasets. For example, Li et al. (2014) enhanced the short-term forecasting accuracy of crude oil prices by developing a multiscale SVR model combined with wave transformation. Fan et al. (2016) further illustrated SVR's adaptability by integrating Independent Component Analysis (ICA) into the model, achieving significant gains in accuracy. Additionally, Shurong & Yulei (2013) showcased the method's superiority over traditional approaches by incorporating dynamic error correction factors into an SVR-based model.

More recent studies have explored cutting-edge applications of SVR, demonstrating its adaptability to evolving market dynamics. Duan et al. (2024) employed SVR alongside the seagull optimization algorithm to predict Brent and WTI crude oil prices, achieving exceptional accuracy and lower error rates compared to alternative models. Karasu et al. (2020) combined SVR with multi-objective optimization techniques to deepen insights into the nonlinear dynamics of crude oil prices, yielding highly precise forecasts.

Comparative analyses in the literature reinforce SVR's strong performance across diverse applications. Yu et al. (2017) established that SVR consistently delivers superior accuracy compared to traditional models such as ARIMA and Markov transition models. Similarly, Suryani & Fadhilla (2024) confirmed the method's effectiveness in forecasting Indonesian crude oil prices, particularly in volatile market conditions. These studies collectively highlight SVR as a powerful, reliable, and flexible tool for tackling complex forecasting challenges across various sectors.

Despite the critical role of maritime transportation in global trade and its contributions to economic growth and sustainability, a significant research gap persists regarding the trends and future implications of its two principal segments—crude oil and dry cargo shipping. While existing studies predominantly focus on the operational aspects, environmental impacts, and market volatility of crude oil transport, comprehensive analyses addressing the sector's long-term outlook remain limited. Similarly, although dry cargo shipping underpins many industrial and agricultural supply chains, its future prospects have not been adequately investigated. Moreover, methodological limitations further exacerbate these gaps, as existing forecasts often rely on traditional econometric methods rather than advanced predictive models. Addressing this gap is essential for developing comprehensive strategies that enhance the efficiency, sustainability, and adaptability of the maritime transportation sector.

Furthermore, the necessity for a long-term perspective is underscored by emergent regulatory measures aimed at reducing maritime emissions (IMO, 2023), ongoing fluctuations in global economic cycles (World Bank, 2021), and the accelerating pace of technological innovation in shipping logistics and vessel design. Anticipating these changes is crucial not only for optimizing current operations but also for shaping resilient and future-proof strategies across the maritime industry.

This study aims to forecast future trends in maritime transportation, focusing on crude oil and dry cargo shipping. These two segments are selected because they represent the largest share of global seaborne trade, making them crucial to understanding long-term maritime transport dynamics (UNCTADstat, 2024). Unlike some analyses that treat different cargo types as interdependent variables, this study examines crude oil and dry cargo transportation separately, recognizing that their market drivers and influencing factors are distinct (Özispa et al., 2024; Jia, 2018). While crude oil transport is shaped by energy policies, fossil fuel demand, and geopolitical factors, dry cargo transportation is predominantly driven by industrial production, agricultural supply chains, and infrastructure investments (Sharma & Yadav, 2020; Zhu & Hsieh, 2024). By employing Support Vector Regression (SVR)—a robust predictive modeling technique that has been underutilized in forecasting maritime transport volumes—this study fills a methodological gap while simultaneously offering practical implications for maritime logistics management. By offering insights that bridge academic research and practical applications, this study aims to provide a solid methodological foundation for improving decision-making and operational strategies in maritime logistics.

2. Method

2.1. Data

The data used in this study spans the years 1970 to 2021 and was obtained from the statistical platform of the United Nations Conference on Trade and Development (UNCTADstat, 2024). The datasets analysed in this study are as follows:

- Crude Oil Loaded: Annual data on the volume of crude oil transported (in million tons)
- Dry Cargo Loaded: Annual data on the volume of dry cargo transported (in million tons)

Certain limitations must be acknowledged while analyzing the results of this study. The analysis was confined to data from 1970 to 2021. The study specifically concentrated on the transportation of dry cargo and crude oil. While these two cargo categories represent the predominant portion of global marine trade, the maritime industry include a range of additional cargo types. Third, about data reliability, this analysis employs data from UNCTAD, a reputable and globally esteemed source. This method alleviates apprehensions regarding data precision and enhances the uniformity of the outcomes. Ultimately, the study only partially examines the effects of external causes, including global economic crises, geopolitical upheavals, and unforeseen catastrophes like the COVID-19 epidemic. These factors may result in considerable variations, especially in volatile industries like crude oil transportation, and are sources of uncertainty that must be accounted for in future estimates. The analysis was conducted using the R programming environment.

2.2. Methodology

SVR is a machine learning method designed to perform predictions on nonlinear and complex data structures. Originally proposed by Vladimir Vapnik and colleagues, this method is an extension of the Support Vector Machines (SVM) algorithm tailored for regression problems (Vapnik, 1995). The primary goal of SVR is to maintain prediction errors within a defined tolerance range (ϵ) while enhancing generalization capacity. These characteristics make SVR particularly popular for nonlinear data structures, such as time series and financial data analysis (Schölkopf & Smola,2004).

SVR operates by mapping input data to a higher-dimensional feature space using a nonlinear function, enabling the construction of a linear regression function in this space. This approach transforms a nonlinear regression problem in the low-dimensional input space into a linear regression problem in the high-dimensional feature space, where the solution is determined (Demirezen & Çetin, 2021). The aim of SVR is to minimize the error between the predicted value (f(x)) and the actual value (y) ensuring that the data is modelled within a specified tolerance (ϵ) around a linear or nonlinear hyperplane. This process is formulated as an optimization problem.

- Prediction Function

The prediction function is defined as follows:

$$f(x) = w \cdot \phi(x) + b \tag{1}$$

Where:
w: The weight vector.
$\phi(x)$: The input data mapped to a higher-dimensional feature space using a kernel function.
b: The bias term of the model.

- Objective Function

SVR minimizes the following objective function:

$$\min_{w,b,\xi,\xi} \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}(\xi_i + \xi_i^*) \tag{2}$$

In This Equation:
$\|w\|^2$: This term minimizes the complexity of the hyperplane.
C: The regularization parameter, which controls the trade-off between model accuracy and generalization.
ξ_i and ξ_i^*: Positive slack variables that represent errors outside the ϵ\epsilonϵ-tubes between the predicted and actual values.

- Constraints

SVR ensures that the predicted function f(x) remains within the ϵ\epsilonϵ-tolerance, while minimizing deviations that exceed this tolerance. This is expressed through the following constraints:

$$y_i - f(x_i) \le \epsilon + \xi_i \tag{3}$$
$$f(x_i) - y_i \le \epsilon + \xi_i^* \tag{4}$$
$$\xi_i \text{ , } \xi_i^* \ge 0 \tag{5}$$

These constraints aim to ensure that the predicted values remain within a specified error tolerance (ϵ) while minimizing the errors (ξ_i ve ξ_i^*) that fall outside this tolerance.

- Lagrange Transformation

The optimization problem is transformed into a dual problem using Lagrange multipliers (a_i, a_i^*). The solution is expressed as:

$$f(x) = \sum_{i=1}^{n} (a_i - a_i^*) K(x_i, x) + b \tag{6}$$

Where:
$K(x_i, x) = \phi(x_i) + \phi(x)$: The kernel function, representing the similarity between two data points.
a_i,a_i^*: Lagrange multipliers, which are nonzero only for support vectors.
b: The bias term of the model.

- Kernel Functions

SVR uses kernel functions to enhance accuracy in nonlinear datasets. Commonly used kernel functions include:
Linear Kernel:

$$K(x_i, x_j) = x_i . x_j \tag{7}$$

RBF (Radial Basis Function) Kernel:

$$K(x_i, x_j) = \exp(-\gamma \| x_i - x_j \|^2 \tag{8}$$

Polynomial Kernel:

$$K(x_i, x_j) = (x_i . x_j + c)^d \tag{9}$$

Where:
c: A constant term.
d: The degree of the polynomial.
Through this mathematical structure, SVR demonstrates a strong generalization capability in both linear and nonlinear datasets. When hyperparameters (C, ϵ, γ) are carefully optimized, SVR delivers effective results, particularly for complex and nonlinear data structures. This makes SVR a valuable tool in various fields, including energy markets, transportation indices, and time series analysis.

3. Results

Historical trends in crude oil and dry cargo volumes loaded globally between 1970 and 2020, as measured in million metric tons, are illustrated in Fig. 1. Volume is represented by the vertical axis, which spans from 1,000 to 9,000 million metric tons, while the horizontal axis encompasses the 50-year range. Crude oil transportation was subject to fluctuations, culminating in a significant decline in the early 1980s, after which it gradually recovered and stabilized in the following decades. In contrast to crude oil, dry cargo transportation experienced a consistent upward trajectory, with a substantial increase in the mid-1990s, ultimately attaining an estimated 8,000 million tons by 2020. Dry cargo, in contrast, exhibited a long-term expansion trend, while crude oil transportation did not exhibit sharp increases beyond the 2,500 million-ton range. Dry cargo volumes demonstrated resilience, with only minor fluctuations, while crude oil transportation experienced temporary declines, particularly in the early 1980s and post-2015, reflective of market-driven volatility.

Figure 1. Crude Oil and Dry Cargo Raw Data

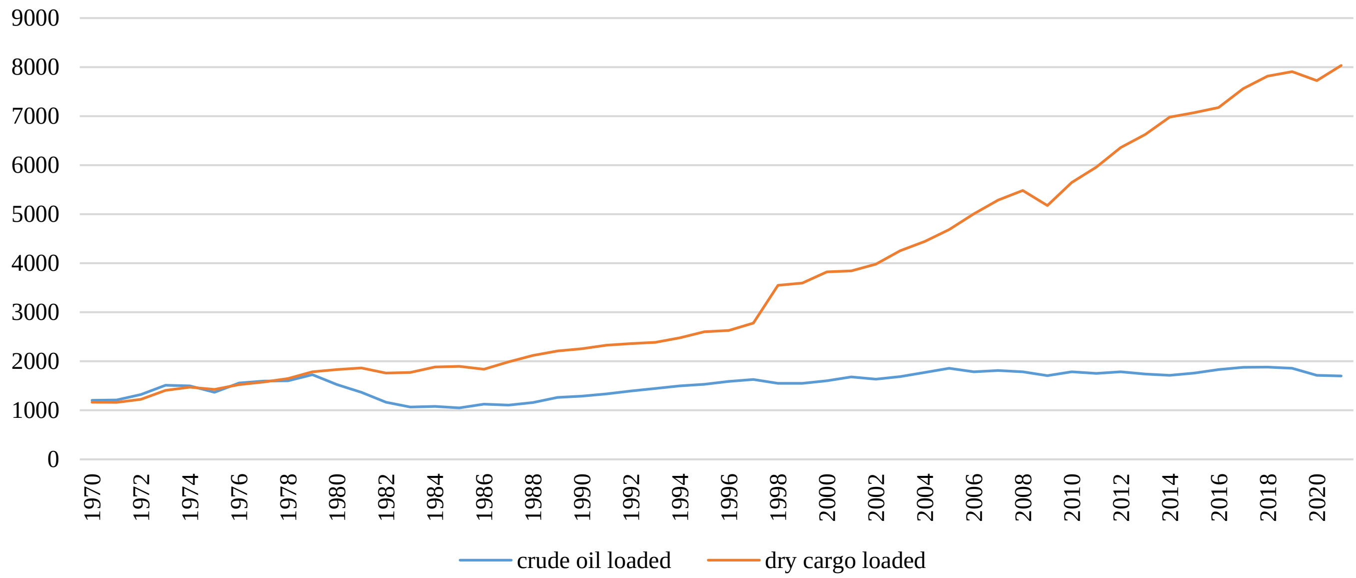


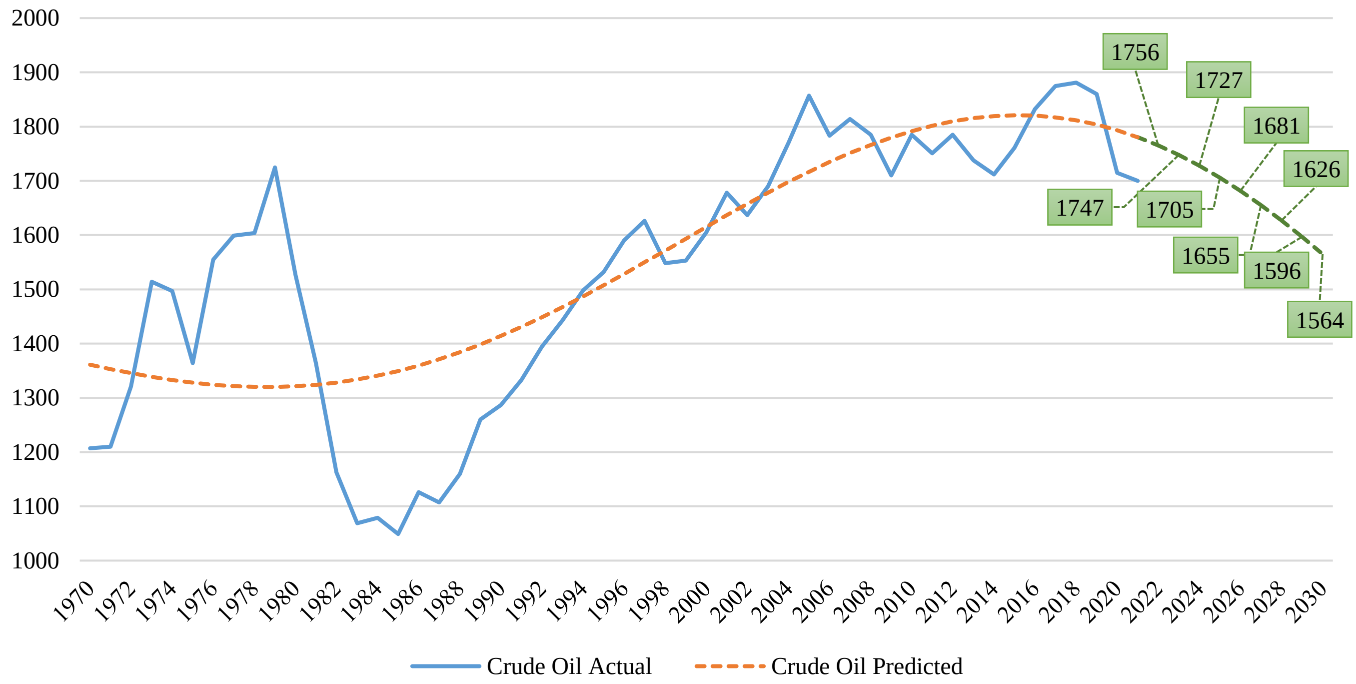
Table 1 presents basic statistical analysis results for crude oil and dry cargo transportation data up to 2021. For crude oil transportation, the minimum value was recorded as 1.049 million tons, and the maximum value reached 1.881 million tons. The average value was calculated at 1.539 million tons, with a standard deviation of 246,92 million tons. These results indicate notable periodic fluctuations in crude oil transportation. On the other hand, for dry cargo transportation, the minimum value was recorded at 1.162 million tons, while the maximum value reached 8.033 million tons. The average value was calculated at 3.680,23 million tons, with a standard deviation of 2.216,70 million tons. The high standard deviation in dry cargo transportation suggests a broader range of variability for this type of transportation. These statistics highlight the dynamic nature of the maritime transportation sector and emphasize the need to account for this variability in modeling studies.

Table 1. Basic Statistical Measures for Crude Oil and Dry Cargo Transportation

	Minimum	Maximum	Mean	Standard Deviation	Count
Crude Oil	1049	1881	1539	246,9175	52
Dry Cargo	1162	8033	3680,231	2216,703	52

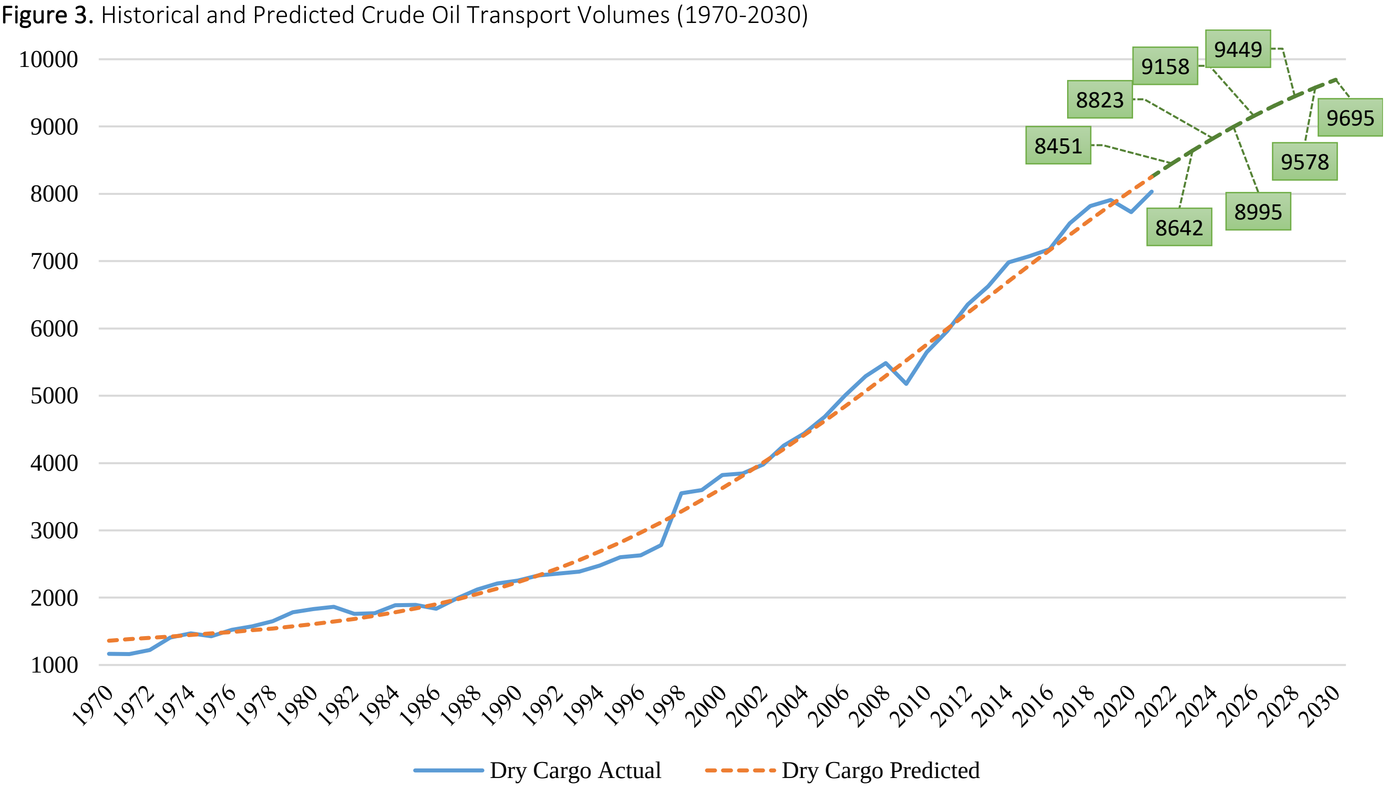
The data on crude oil transportation from 1970 to 2021, along with projections for the 2022–2030 period, have been analysed (see Figure2). In the 1970s, the volume of crude oil transported was approximately 1.360 million tons, which showed a decline by the 1980s. From the mid-1980s onward, the transported volume began to rise again, peaking around 2015 at approximately 1.820 million tons. However, as of 2021, this volume started to decrease, and the downward trend is expected to continue through the 2022–2030 period. According to model projections, the volume of crude oil transported is anticipated to decline to approximately 1.565 million tons by 2030, representing an 8% decrease. The observed and projected values indicate that the model successfully captures the overall trends.

Figure 2. Historical and Predicted Crude Oil Transport Volumes (1970-2030)



The data and projections for dry cargo transportation from 1970 to 2030 indicate a long-term growth trend in the sector (see Figure 3). In the 1970s, the volume of dry cargo transported was approximately 1,361 billion tons, increasing steadily each year to reach 8,835 billion tons by 2021. Notably, the growth rate accelerated during the 2000s, with a significant increase in transported cargo volumes during this period. Model projections for the 2022–2030 period suggest that the growth trend in dry cargo transportation will continue. The projected volume for 2022 is approximately 8,642 billion tons, with expectations for this figure to rise to 9,695 billion tons by 2030. This increase corresponds to about 20,6%.

Figure 3. Historical and Predicted Crude Oil Transport Volumes (1970-2030)



The performance of the applied model was evaluated separately for crude oil and dry cargo transportation data (see Table 2). For crude oil transportation, the model's prediction accuracy was found to be adequate, with a Mean Absolute

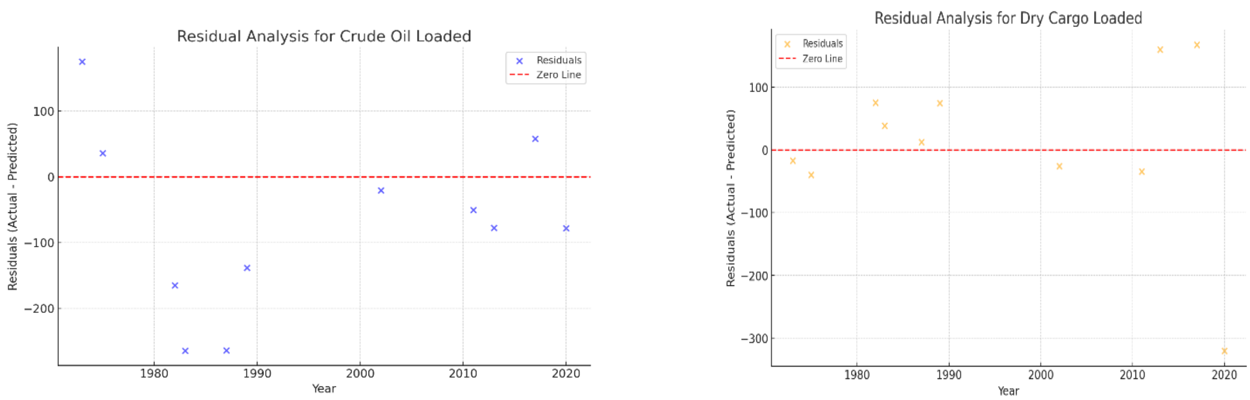
Error (MAE) of 120,77 million tons, a Mean Squared Error (MSE) of 21.523,41 million tons², and a Root Mean Squared Error (RMSE) of 146,71 million tons. The R^2 score was calculated as 0,7204, indicating that the model explains approximately 72% of the variance in crude oil transportation data. However, it was observed that the model's performance is somewhat constrained by the volatility of the energy sector and other complex variables.
For dry cargo transportation, the model demonstrated exceptionally strong performance. The MAE was calculated at 87,83 million tons, the MSE at 15.707,25 million tons², and the RMSE at 125,33 million tons. The R^2 score was determined to be 0,9974, indicating that the model accounts for 99% of the variance in dry cargo transportation data. This high level of accuracy highlights the model's reliability in predicting dry cargo transportation volumes.
Overall, while the model performed impressively for dry cargo transportation, its accuracy for crude oil transportation was somewhat limited due to the dynamic nature of the sector (Charles & Darné, 2014). Nevertheless, the model exhibited strong predictive capabilities for both types of transportation, with particularly remarkable results for dry cargo.

Table 2. Model Performance Metrics for Crude Oil and Dry Cargo Transportation

Metric	Crude Oil Loaded	Dry Cargo Loaded
Mean Absolute Error (MAE)	120,7717	87,83429
Mean Squared Error (MSE)	21523,41	15707,25
Root Mean Squared Error (RMSE)	146,7086	125,3286
R^2 Score	0,720398	0,997446

The residual analysis results for the model's performance (see Figure 4) were visualized by examining the differences between predicted and actual values. For crude oil transportation, the residual analysis revealed that prediction errors were generally within the range of ±200 million tons, and it was observed that the model's accuracy was partially constrained by the volatility of the energy sector.
For dry cargo transportation, the residual analysis indicated that errors were within the range of ±100 million tons, demonstrating higher accuracy for this dataset. However, an exceptional error was observed for dry cargo transportation in 2020, which is thought to have resulted from sudden changes in the transportation sector due to the global disruption caused by the COVID-19 pandemic. The pandemic led to significant shifts in supply chains, including port closures, labour shortages, and demand fluctuations, which collectively impacted dry cargo transportation volumes during that year (Michail & Melas, 2020).

Figure 4. Residual Analysis Results



The residual analysis indicates that the model's performance was generally consistent, with deviations aligning closely to the zero-error line. This suggests that the applied SVR model effectively captures trends in maritime transportation, despite some limitations observed in the crude oil sector.

4. Discussion

Dry cargo transportation has shown a consistent growth trend. Since the 1970s, the increasing volume of transported cargo has been linked to the diversification of global trade and advancements in infrastructure investments. Han et al. (2014) highlighted the effectiveness of SVR in short-term predictions and price risk management for the BDI, findings that align with this study's high R^2=0.9974 accuracy rate for dry cargo transportation. Similarly, Bao et al. (2016) demonstrated the effectiveness of SVR models based on macroeconomic indicators in understanding market trends. The model in this study also demonstrated similar accuracy with low error rates, successfully forecasting growth trends in dry cargo transportation.

The anticipated increase in dry cargo transportation aligns with trends identified in the literature, emphasizing that this growth is shaped by the expansion of global trade, industrial developments, and the impact of infrastructure investments. Özispa et al. (2024) projected an 11,1% increase in dry cargo volumes by 2030, highlighting the sector's long-term growth potential. Similarly, Goulielmos (2018) underscored the importance of predicting market cycles in order to adapt to rising trade demands; this aligns with the 20,6% growth in dry cargo volumes projected in this study. These findings once again highlight the critical importance of infrastructure developments, such as the construction of deep-water ports and the implementation of advanced logistics systems, in meeting increasing demand. Furthermore, Zhu & Hsieh (2024) emphasized that efficient management of supply chains will be pivotal in supporting future growth in dry cargo transportation.

The decline in crude oil transportation observed in this study reflects broader trends in the energy market, as highlighted in the literature. Jia (2018) noted that the global shift towards renewable energy and green logistics practices is driving reductions in crude oil transportation demand. Özispa et al. (2024) similarly projected a 10,7% decline in crude oil volumes by 2030, which aligns with this study's findings of an 8% decrease over the same period. These trends underline the growing need for diversification in the maritime transport sector. For instance, Duan et al. (2024) emphasized the importance of transitioning fleets towards transporting alternative energy sources, such as LNG or renewable energy equipment, as a strategic response to these shifts. Furthermore, Sharma & Yadav (2020) highlighted the volatility of the energy market as a key challenge, suggesting that innovative and flexible operational strategies are essential to maintain competitiveness. Collectively, these findings demonstrate the pressing need for the crude oil transportation sector to adapt to evolving energy demands and prioritize sustainability-driven solutions.

The instability in the crude oil transportation sector significantly complicates achieving high prediction accuracy. While Herrera et al. (2018) demonstrated that integrating Independent Component Analysis (ICA) with SVR can enhance forecasting performance, the R^2=0.7204 accuracy rate achieved in this study highlights the limitations imposed by the inherent unpredictability of the energy sector. The sector's sensitivity to external shocks was particularly evident during the COVID-19 pandemic, which caused dramatic fluctuations in crude oil demand and prices. Michail & Melas (2020) highlighted how the pandemic disrupted tanker markets through demand-driven shocks, while Bourghelle et al. (2021) emphasized the unprecedented price fluctuations triggered by simultaneous supply and demand disruptions. Similarly, Ogoun (2021) noted the dual impact of the pandemic on transportation and storage, creating additional risks for the shipping sector. These findings underscore the importance of forward-looking strategic planning to mitigate risks in a sector as sensitive to external shocks as crude oil transportation.

5. Conclusion

This study analyses historical trends in maritime transportation for crude oil and dry cargo, providing future projections for these two key segments. Utilizing the SVR method, the analysis forecasts a decline in crude oil transportation and a significant increase in dry cargo transportation by 2030. The findings offer valuable insights for strategic decision-making in areas such as operational planning and infrastructure investments within the maritime industry. Additionally, the study highlights the need for companies and stakeholders to adapt to shifting market dynamics to ensure competitiveness and sustainability in the evolving maritime sector.

The findings reveal the necessity of reshaping operational strategies to align with future market dynamics. Dry cargo transportation is projected to increase by approximately 20,6%, while crude oil transportation is expected to decline by 8%. These changes require shipping companies to optimize their fleet composition, improve operational efficiency, and adapt to emerging market opportunities. Investments in larger and more efficient vessels are essential to meet the rising demand for dry cargo. In contrast, the anticipated decline in crude oil transportation presents an opportunity to diversify into alternative market segments, such as renewable energy equipment or LNG transportation.

To maintain competitiveness and address global environmental concerns, shipping companies must prioritize sustainability. Transitioning to energy-efficient vessels and adopting low-carbon fuels will not only reduce emissions but also ensure compliance with tightening international regulations. These efforts are critical for supporting the long-term viability of maritime operations.

The decline in crude oil transportation further emphasizes the need to repurpose existing tanker fleets for sustainable operations. Long-term collaborations with cargo owners and supply chain stakeholders can help stabilize operations in this volatile market. Additionally, pooling resources to finance advanced vessels will enable shipping companies to capitalize on growth opportunities in the dry cargo sector.

Shipbuilding companies must go beyond responding to current demands by developing innovative solutions tailored to future needs. High-capacity, durable, and efficient vessels designed for the increasing demand for dry cargo are essential for seizing growth opportunities. Furthermore, vessels optimized for alternative cargo types, will address shifting market demands while providing a competitive edge. Retrofitting existing tanker fleets to accommodate diverse cargo segments also presents significant economic and operational benefits.

Port operators must enhance and modernize their infrastructure to support the increasing demand for dry cargo transportation. Developing deep-water facilities, implementing efficient loading, and unloading systems are crucial for operational efficiency. Additionally, diversifying services to handle alternative cargo types, such as renewable energy equipment, will position ports as pivotal hubs in the evolving maritime supply chain.

While this study demonstrates the applicability of the SVR method for forecasting trends in maritime transportation, future research could explore integrating hybrid models that combine machine learning approaches with macroeconomic and trade data to improve predictive accuracy. Additionally, investigating the regional variations in the increasing demand for dry cargo and declining trends in crude oil transportation would provide a deeper understanding of global maritime dynamics. Research could also focus on strategies for adapting existing tanker fleets to alternative cargo types, such as renewable energy equipment or LNG, aligning with the changing needs identified in this study. Lastly, future studies might examine the long-term impact of sustainability-driven policies on ship design, fleet management, and port operations to support the industry's transition toward greener practices.

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