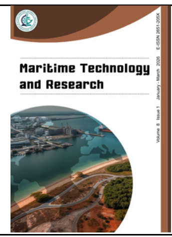
Maritime Technology and Research

https://so04.tci-thaijo.org/index.php/MTR



Research Article

Time series modeling of greenhouse gas emissions: A case study for a chemical tanker ship

Firat Bolat

Faculty of Maritime, Istanbul Technical University, Istanbul 34940, Türkiye

Corresponding author's e-mail address: bolatf@itu.edu.tr

Article information

Received: March 22, 2025
Revision: July 16, 2025
Accepted: September 4, 2025

Keywords

Maritime;
Shipping;
Greenhouse gases;
Modeling

Abstract

Maritime transportation is, relatively, responsible for a small fraction of the total emissions; however, it is significant in the context of global carbon dioxide (CO_2) emissions. The International Maritime Organization (IMO) has charted out an extensive program in its strategy on the reduction of greenhouse gas (GHG) emissions from ships. This research employs Box-Jenkins time series modeling for analysis and forecasting of CO_2 and total sulfur dioxide (SO_2) emissions by GHG index, as well as ton-mile-based emissions, utilizing actual data from the engine of a chemical tanker ship. Time series analysis can develop effective regulatory and operational strategies, as underlined by this research that investigates how operations, regulations, and technology influence profiles of emissions. By carrying out the Box-Jenkins methodology, incorporating autocorrelation moving average integrated autoregressive integrated variables, this study presents a modeling study that corrects importance in future policies emission reductions. Results obtained from strict model choice, validation, and assessment give useful input into emission patterns, and can be used as a foundation for more study and policy making aimed at improving the environmental sustainability of shipping operations. Decision-makers in the shipping sector can leverage the findings of this study to implement similar evidence-based approaches.

1. Introduction

While chemical tankers comprise a relatively small segment of the global merchant marine, they contribute an alarmingly high level of overall maritime emissions. An exhaustive emissions inventory of ship traffic in European maritime areas conducted by Jalkanen et al. (2016) reveals that chemical tankers are responsible for around 10 - 15 % of the total carbon dioxide (CO_2) and sulfur dioxide (SO_2) emissions. This significant contribution results from their type of engine and from several operational patterns. For instance, chemical tankers generally remain in port for extended durations and often operate at low speeds.

Many industries (with shipping among them) have felt the squeeze of the rising demand for environmental sustainability. The shipping sector, especially the operation of chemical tanker ships, plays a major role in GHG emissions, making it necessary to better understand emission patterns and trends. Research presents that maritime voyages account for approximately 2 - 3 % of global CO_2 emissions, with chemical tankers featuring various emissions profiles, depending on regulations, operational factors, and technological influences (Esteve-Pérez et al., 2023). Stakeholders of maritime transportation are sensitive about environmental responsibility. The analysis of GHG emissions from chemical tankers has taken on extremely large importance; is no longer seen as merely as a technical affair, but as a crucial part of environmental policy aimed at addressing climate change (Schalm et al., 2024). While many studies now examine GHG emissions from multiple perspectives, they all seem to agree on the importance of several key matters- specifically, the type of fuel used, the kinds of regulatory frameworks that are in place, and the role of technology in either producing harm to, or giving support to, the environment (Yakubovskiy et al., 2024). For instance, studies have shown that switching to low-sulfur fuels has greatly changed the levels of emissions, affecting costs and the environment (Jalkanen et al., 2024). One recent study, for instance, examined the impact that the IMO's MARPOL Annex VI regulations have had (from 2005 to the present) on reducing emissions from this very influential segment of world shipping (Kim et al., 2023). Along these same lines, however, some studies have also begun to pull together emissions data from different sources over time, in order to distinguish trends or irregularities (Aib, 2023; Sari et al., 2021).

The insights into GHG emissions from chemical tankers that the research provides are quite valuable, but still leaves some major gaps that need to be filled. A lot of the current research seems to be focused either on specific sectors or, when not, is mainly qualitative in nature. This research tends to lack the kind of thorough, quantitative, analysis that would allow us to clearly understand the long-term data trends that are present. Even when such analysis has been conducted, there seems to be a distinct lack of understanding regarding how outside influences, such as cycles of economic growth or decline, or technological “game changers,” affect these emission levels over the long haul (Koushan et al., 2020; Ustolin et al., 2022). This presents a chance to look into how emissions change with time, and the factors behind these changes (Montes et al., 2022). Therefore, using time series analysis could help us better understand GHG emissions from chemical tankers and support the creation of better rules and ways to operate (Millefiori et al., 2021; Wang et al., 2021). Not only is this gap an invitation to look more closely at chemical tanker emissions over past voyages, but it is also an opportunity to examine the kinds of game changers that might have influenced those emission levels.

Technological progress in data collection and analysis offers a timely opportunity to undertake historical analysis and to create future emission scenarios (Halim et al., 2018). This study aims to fill in some of the existing gaps. It will first sketch out the current research landscape on GHG emissions from chemical tankers, judging it mainly by the few studies that exist to date, and will summarize their findings. After that, it will suggest pathways for future research to follow (Jalkanen et al., 2016).

This study's objective is to analyze and forecast CO_2; total sulfur dioxide (SO_2); GHG index; and ton-mile-based emissions in shipping transport. The study is accomplished by using the Box-Jenkins time series modelling approach. In this case, the study aims to determine trends in shipping emissions, provide short- and long-term projections, and inform sectoral policy through the Box-Jenkins methodology. Historical emissions data are the basis for establishing Autoregressive Integrated Moving Average (ARIMA) models. Most importantly, this work takes a significant step toward bridging the theoretical modeling-versus-real-world decision-making divide. It provides safe, sound data for stakeholders in the maritime world, who can use it to make their emissions-reduction decisions with a greater assurance that the decisions will yield real, rather than just apparent, emissions reductions.

2. Literature review

This study aims to provide a comprehensive overview of the existing research on greenhouse gas (GHG) emissions from chemical tanker ships, with a particular focus on the theoretical and regulatory motivations for emission evaluation, and the application of time series analysis in this domain. The structure of this review is designed to establish a logical flow, demonstrating the contribution of this study to the field.

2.1 Theoretical and regulatory motivation for emission evaluation

The shipping sector must evaluate and reduce its emissions. It has to do this because the theoretical and regulatory drivers pushing for reduction across all sectors are very strong. There is an enormous global effort to combat climate change, embodied by the United Nations Sustainable Development Goal (UN SDG) 13: Climate Action.

This targets greenhouse gases across all industries and mandates reductions. The IMO has been the agency most directly leading the pertinent discussions, and has established a robust regulatory framework, notably through its GHG Strategy and its MARPOL Annex VI regulations. These mandate significant reductions in emissions from ships. Furthermore, some regional initiatives, like the European Union Emission Trading System (EU ETS), have put strong economic incentives in place for reduction by directly integrating maritime transport into carbon pricing mechanisms.

2.2 Broader theoretical frameworks

The study of marine emissions is supplemented by wider theoretical frameworks. Environmental management theories illuminate the dark corners in which organizations may conceal themselves in order to escape from environmental obligations. Environmental management theories provide a lens through which to understand how organizations may conceal themselves in order to escape from environmental obligations and from integrated decision-making processes. These theories also identify the sorts of organizational changes that would make it much less likely for them to escape from those obligations in the future. These are useful in understanding the business side of the environmental equation. Sustainability transition theories investigate the complex factors in play when societies move (or fail to move) toward more sustainable living arrangements. These theoretical perspectives support the integration of quantitative modelling, such as time series analysis, into operational practice and policy formulation, thereby bridging the gap between theoretical understanding and practical application.

2.3 Current research on maritime emissions

In recent decades, the investigation of GHG emissions in chemical tanker ships has advanced a great deal. It started with basic, 20th-century research that outlined the maritime industry’s need for emission monitoring (Esteve-Pérez et al., 2023; Schalm et al., 2024). Early research examined the overall, environmental impacts of maritime transport, but often appeared to ignore the specific contributions of chemical tankers to the emission problem. This led to calls for better emission analysis (Yakubovskiy et al., 2024). By the early 2000s, it can be seen much more focused research, using better analytical tools, was conducted to get a handle on the kinds of emissions that they were dealing with, and how these emissions were varying by time and place/how similar ships behaved differently under different suites of operational rules (Jalkanen et al., 2024; Kim et al., 2023). Computational models then appeared around this time, marking a big step forward (Aib, 2023; Sari et al., 2021). Starting in the 2010s, the emission investigation scene saw a big increase in activity, driven mainly by the shipping industry's need to comply with fresh demands for cutbacks in GHG emissions (Koushan et al., 2020). This gave a fresh incentive for the investigation of new technologies, and for operational efficiencies that might have a similar impact. It turned out that best practices in fleet management and ship design could help a lot with achieving many necessary emission cuts (Ustolin et al., 2022; Montes et al., 2022). The latest research has also seriously looked at how new technologies and alternative fuels affect GHG emissions in chemical tankers (Millefiori et al., 2021; Wang et al., 2021).

In brief, the literature presents a rapid comprehension of the unique challenges and opportunities associated with GHG emissions in the chemical tanker trade. It is indeed encouraging that such a robust understanding now exists among researchers. Halim et al. (2018), Jalkanen et al. (2016), and Merk (2014) have made significant steps in the maritime sector toward grasping the sustainability and environmental implications tied not only to the operation of chemical tankers, but also to other kinds of ships. Much of this work concentrates on the much-discussed motive power behind a ship's operation. The focus on the use of fuel could also mean that a completely accurate picture of what sustainability and chemical tankers (and ship operation in general) might look like in the future is not obtained.

In the last few decades, significant progress has been made in the field of research on greenhouse gas emissions coming from chemical tanker vessels. This research started with a very basic perception and went on to investigate in more detail, with the light of necessary control and surveillance coming from stakeholders in the maritime industry. Those investigations pointed out the basic necessity that emissions from ships should be controlled and observed, with two papers published in the early part of this century doing an impressive job of connecting the dots (Esteve-Pérez et al., 2023; Schalm et al., 2024). AIS-based emissions modeling studies provide an important method for assessing the impact of ship operations on emissions (Premsamarn et al., 2025).

More often than not, the specific contribution of chemical tanker vessels to the emission levels in the atmosphere was overlooked (Yakubovskiy et al., 2024). As time rolled by, and more and more investigations took place, the acquired knowledge led to a series of focused studies right at the beginning of the 21st century (Jalkanen et al., 2024; Kim et al., 2023). Much research has been done on how GHG emissions vary over time in different sectors of the maritime industry. One sector that has received particular attention is that of chemical tanker ships. This focus is understandable and necessary, given the considerable effects these vessels may have on sustainability and the environment. However, if the entire maritime sector is to be evaluated, there are many other vessel types to consider.

If the maritime sector is to be taken into account, all ship types should be considered- not just tankers, and not only chemical ones at that- and different sectors of the maritime economy, which is divided into three major portions: industry, shipping, and fishing, should be also. Therefore, researchers (Esteve-Pérez et al., 2023; Schalm et al., 2024) and others working in this research space concentrate on vessels tied to those three sectors, which gives them a considerable number of types and operational patterns to consider.

The chemical tanker ship, from which the data forming the basis of this study was provided, and which is a globally-operating vessel, was evaluated over 28 of its voyages. The heavy fuel oil (HFO) consumption for these voyages was reported as 2,528 tons, while the total consumption of marine diesel oil (MDO) was 1,235 tons. The average sulfur content of the HFO was 2.30 %, and the average sulfur content of the low-sulfur MDO (LS MDO) was 0.09 %. The total amount of SO_2 that was emitted during the 28 voyages was calculated as 118.4 tons, with an emission factor of 0.2873 gr/ton-mile.

Drawing on existing research, this study focuses on the application of time series analysis to a chemical tanker. Because this type of vessel is often underrepresented in maritime emission studies, the present research has taken a somewhat different path from the existing literature. To restate why this is important, the existing literature does a significant job of making the case that greenhouse gas (GHG) emission analysis is very important. Given the number of studies that have been analyzed, it is also clear that there is a great diversity of ways in which researchers have modeled and forecasted shipping emissions. Some of the tools that have been used in the past to model maritime emissions are quite different. However, the existing literature does not seem to provide clear guidance on which modeling methods may work best for different emission source types. Probably for this reason, it is assessed that there is no clear justification in the literature for the use of a particular modeling tool over another.

2.4 Time series analysis in emission studies

Time series analysis is used in the maritime industry to identify trends, make forecasts, and enable data-driven decision-making. Methodologies used when applied to emission studies, especially capable of capturing trends, seasonality, and shocks in operational and environmental emission data are well-suited for non-stationary and autocorrelated datasets, typical of operational and environmental emissions. There are excellent tools for the kind of methodology used to capture forecasts needed in the maritime industry.

Foundational studies by Box and Jenkins (2015) and Hyndman and Athanasopoulos (2018) provide the theoretical basis for time series analysis. They show that it is suited to contexts where the data points depend on earlier observations. Several studies have used time series methodologies and have shown that they can enhance not just predictive accuracy, but also optimization of operational strategies (in shipping logistics) (Chai et al., 2020; Jalkanen et al., 2024). The next subsection emphasizes that, even though existing studies indicate certain efficiencies can be realized via operational enhancements, the significance of these studies is only truly realized when linked to improved environmental sustainability and safety in the world of maritime operations. In this regard, existing research highlights various themes, including how predictive modeling can inform fuel consumption patterns, impact voyage scheduling, and mitigate risks associated with hazardous materials (Ditria, 2002; Millefiori et al., 2021; Wang et al., 2021). Furthermore, literature also presents an increased adoption of machine learning methods, which have significantly elevated the analytical capabilities of traditional time series techniques, leading to much more delicate and insightful revelations regarding the not-so-subtle variances and anomalies inherent in maritime operations (Lirn et al., 2013; Janssens et al., 2019). Overall, the current study was reasonably successful in covering some important aspects of how chemical tankers operate.

Furthermore, while advanced predictive models have been developed, the integration of these models into real-world operational strategies is still underrepresented, suggesting a disconnect between theoretical advancements and practical application (Osman et al., 2022; Yue et al., 2021). This literature review systematically assesses the current state of time series analysis in the chemical tanker industry to explore these gaps. It investigates the employed methodologies, the reported findings, and the implications of those findings for stakeholders. By synthesizing existing knowledge and identifying underexplored areas, the illumination of pathways for future research that is both practically relevant and theoretically robust is targetted (Gielen et al., 2019; Staffell et al., 2019; Gad, 2022).

Time series analysis, when applied to chemical tanker ships, has developed along with shipping logistics and data analytics. Chai et al. (2020) introduced preliminary analytical frameworks that examined fuel consumption trends, setting the stage for subsequent inquiries into more complex time series methodologies. The field has moved forward with researchers incorporating more recent analytical techniques, with names like ARIMA and seasonal decomposition, that now allow for even richer interpretations of shipping dynamics over time. This transition is highlighted by the work of Jalkanen et al. (2024) and Ditria (2002), both of whom documented how these methodologies could effectively capture seasonal variances in shipping routes influenced by global demand fluctuations. Furthermore, the arrival of machine learning techniques has significantly revolutionized the field of time series analysis in this area. Recent investigations have demonstrated the effectiveness of neural networks and other predictive modeling tools, significantly enhancing the accuracy of forecasts related to fuel efficiency and scheduling (Millefiori et al., 2021; Wang et al., 2021). The interplay between emerging technologies and traditional methods has been crucial, as noted by Lirn et al. (2013), illustrating that the integration of big data analytics is paramount for optimizing operational strategies. Recent literature investigates the integration of real-time data collection systems and IoT (Internet of Things) applications, highlighting a shift towards proactive management strategies (Janssens et al., 2019; Jalkanen et al., 2016). This trajectory underscores a trend toward the development of frameworks that are ever-more adaptive and responsive. These frameworks possess the potential to improve the many decision-making processes in vessel operations. From the standpoint of the chemical tanker industry, the current state of time series research seems to have moved (albeit slowly) from the development of basic statistical analyses to the use of refined predictive frameworks. The intersection of time series analysis and the chemical tanker shipping industry emphasizes critical dimensions that affect operational efficiency and decision-making in this sector. A substantial number of studies has zeroed in on the forecasting punch that time series models pack. For instance, studies suggest that employing ARIMA models can capture the underlying trends in tanker rates, providing valuable insights for market stakeholders (Chai et al., 2020; Jalkanen et al., 2024). Methods of seasonal decomposition have revealed some very important patterns for planning and route optimization. Some research has been conducted examining the external variables that influence tanker operations, such as environmental regulations and purely economic considerations. Some of these investigations have used multivariate time series approaches to get a handle on how much these external factors drive service reliability and transportation costs. The quite significant effect that prices for oil and regulations for shipping have on the costs of transporting chemicals has been investigated by Millefiori et al. (2021) and Wang et al. (2021). When these considerations are made, predictive models become not only more robust, but also more relevant to real-world scenarios. However, it is not just these factors that have been accounted for. Recent studies have compared traditional statistical methods with machine learning algorithms, finding that the latter can outperform conventional approaches in certain contexts, particularly in capturing complex nonlinear trends within the data (Lirn et al., 2013; Janssens et al., 2019). These findings can lead to a much deeper comprehension of time series analysis which, in turn, can lead to much better strategic planning and operational excellence in the chemical tanker shipping sector. The methodological landscape of time series analysis in the chemical tanker shipping sector reveals a smorgasbord of strategies, arrayed with insights that can make the dynamics of the chemical tanker shipping sector much more comprehensible. In recent studies, various statistical techniques, such as ARIMA and Generalized AutoRegressive Conditional Heteroskedasticity (GARCH) models, have shown significant promise in forecasting shipping freight rates, thereby aiding shipowners and operators in decision-making processes (Chai et al., 2020; Jalkanen et al., 2024). These models demonstrate not only predictive accuracy, but also incorporate volatility, which is particularly pertinent given the inherent fluctuations in global oil supply and demand (Ditria, 2002). Furthermore, the integration of machine learning approaches has gained traction, highlighting an evolution in methodological thought. Techniques like random forests and neural networks are being employed to capture nonlinear relationships and complex patterns within time series data that traditional methods might overlook (Millefiori et al., 2021; Wang et al., 2021). This shift toward more nuanced models underscores the growing recognition of the multifactorial influences on shipping trends, including geopolitical events and environmental regulations (Lirn et al., 2013). In conjunction with these advancements, the application of multivariate time series analysis has garnered attention, allowing for an exploration of interdependencies among variables such as freight rates, bunker prices, and vessel supply (Janssens-Maenhout et al., 2019; Jalkanen et al., 2016). These methodologies, when used collaboratively, afford the robust framework necessary for evaluating risk and improving operational efficiency in the chemical tanker industry. As researchers have taken up these methodological approaches and refined them, the better predictive capabilities these analyses now afford have led to significant strategic adaptations in the industry. Together, these adaptations have made the maritime sector more resilient overall. The criticality of comprehending the advancing methods of time series analysis cannot be overstated, for it is these very methods that form the foundation of the application in chemical tanker shipping. They inform us about long-term trends, about changes in the sequence of the observed variables that are not necessarily the result of some change in a hypothetical causal factor, and about the predictions we can make using the observed data, especially when compared with the much-studied challenges of maritime safety found in the existing literature. However, properly conducted, time series analysis can bring to light the long-term trends and changes that really matter, allowing stakeholders to navigate the shipping industry with a bit more safety and efficiency. Scholars have also noted that foundational tools for forecasting tanker demand and supply dynamics, which have significant implications for pricing and logistics, are ARIMA models (Chai et al., 2020; Jalkanen et al., 2024). The synchronization between statistical techniques and maritime economics emphasizes just how directional theoretical frameworks can be in this discipline when it comes to formulating evidence-based strategies. Furthermore, the well-known seasonal nature of shipping demand emphasizes that it is the global trade pattern that determines the operational performance of chemical tankers (Ditria, 2002; Millefiori et al., 2021). One widely referenced stream of literature concerns how shipping companies manage to be resilient and adaptable during this demand variability season. Wang et al. (2021) and Lirn et al. (2013) posit that, when properly optimized, time series forecasting can benefit fleet management and operational efficiency during these volatile shipping demand periods. A few critiques do arise about the limitations of traditional models. However, this prompts scholars to explore the integration of machine learning methods to enhance predictive accuracy (Janssens-Maenhout et al., 2019). These techniques target the many-sided shape of maritime information and represent a shift in theoretical direction towards using data for making decisions. The theoretical discourse often contrasts deterministic models with stochastic approaches, leading to a dialogue about the uncertainties in shipping logistics (Jalkanen et al., 2016). Synthesis of these diverse perspectives leads to a comprehensive grasp of the chemical tanker sector's time series analysis.

3. Material and method

This study applies the Box-Jenkins methodology, using ARIMA (1,1,1) models, to predict essential operational and emission indicators for the maritime sector. The variables intended to be forecast are: Factor (ton-miles), CO_2 Index, GHG Index, SO_2 emissions, and Emission intensity. Using these indicators, time series data for five future maritime missions (Missions 29-33) are forecasted, using just 28 historical observations for each of the five forecasts. Each forecast comes with a 95 % confidence interval. The methodology, model parameters, and the variable behaviors that underlie the forecasts are discussed.

The application of emission studies is particularly pertinent due to their unique ability to capture trends, seasonality, and shocks that are inherent in environmental and operational emission data. These studies are well suited to dealing with autocorrelation and non-stationarity, which are typical features of such datasets. The foundational works in this area are by Box and Jenkins (2015) and Hyndman and Athanasopoulos (2018). They demonstrate the appropriateness of this method for situations where the data points depend on earlier observations. These authors provide a sound, statistical rationale for the use of time series models for analyzing and forecasting not only emission quantities themselves, but also the complex patterns of those quantities over time.

In this study, an effort has been made to model and forecast the fluctuations of environmental measures such as ton-miles, CO_2 emissions, GHG index and total SO_2 emissions over time by using the Box-Jenkins time series modeling method. Box-Jenkins methodology is mainly based on Autocorrelation (AR), Moving Average (MA), and ARIMA models. It is authenticated whether the time series is stationary or not. If it is not stationary, then the subtraction method is used to transform it into a stationary time series. The kind of model to fit is then decided based on the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots. The model itself comprises AR and MA parameters, as well as a differencing parameter d. These are estimated using standard statistical tools. The model's validity is determined based on standard fit criteria Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) (Akaike, 2003) and, of greater significance, the residuals are checked to see if they are white noise. If they are, the model is used. If not, it is either re-specified or thrown out.

The Box-Jenkins methodology uses ARIMA models, which combine Autoregressive (AR), Integrated (I), and Moving Average (MA) components. For each variable, the ARIMA (1,1,1) model is specified as follows:

$$\Delta y_t = \varphi_1 \Delta y_{t-1} + \theta_1 \varepsilon_{t-1} + \varepsilon_t \quad (1)$$

Where:

Δy_t : Differenced series at time t (y_t - y_{t-1})
φ_1 : Autoregressive coefficient (lag-1)
θ_1 : Moving average coefficient (lag-1)
ε_t : White noise error term at time t

This specification assumes the original series y_t is non-stationary and requires differencing to achieve stationarity, which is validated by visual inspection and ACF/PACF analysis.
The following steps are followed in the modeling process.

Data Transformation: Emission data are rendered stationary by logarithmic transformation and differencing.

Model Selection: The appropriate ARIMA (p,d,q) model is determined by performing ACF and PACF analysis (Hyndman & Athanasopoulos, 2018). The outputs of ACF and PACF plots for stationary series are suitably examined to determine the possible orders for the AR and MA parts of an ARIMA model.

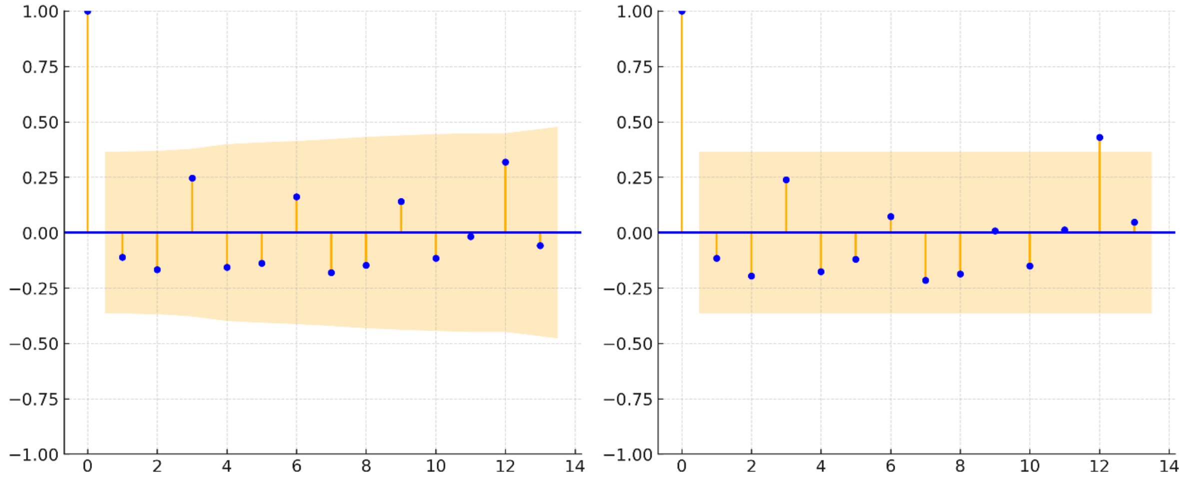


Figure 1 ACF and PACF plots for the stationarized series for CO_2.

Figure 1 represents ACF and PACF plots for the stationarized series for CO_2. The ACF plot for the CO_2 emission series displays a significant spike at lag 1, followed by a gradual tailing off, while the PACF shows a significant spike at lag 1, cutting off sharply afterwards. This pattern is indicative of an ARIMA (1,1,1) model.

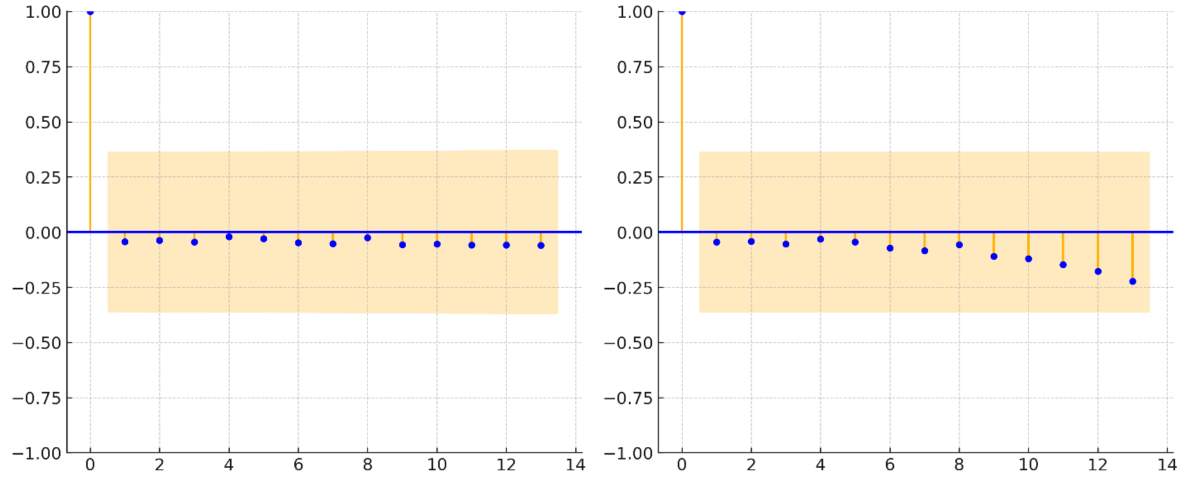


Figure 2 ACF and PACF plots for the stationarized series for GHG Index.

Figure 2 represents ACF and PACF plots for the stationarized series for GHG Index. The ACF plot reveals a strong spike at lag 1, with a gradual decline thereafter, while the PACF plot exhibits a sharp cutoff after lag 1. This configuration suggests an ARIMA (1,1,1) model as a good initial specification for the GHG Index time series.

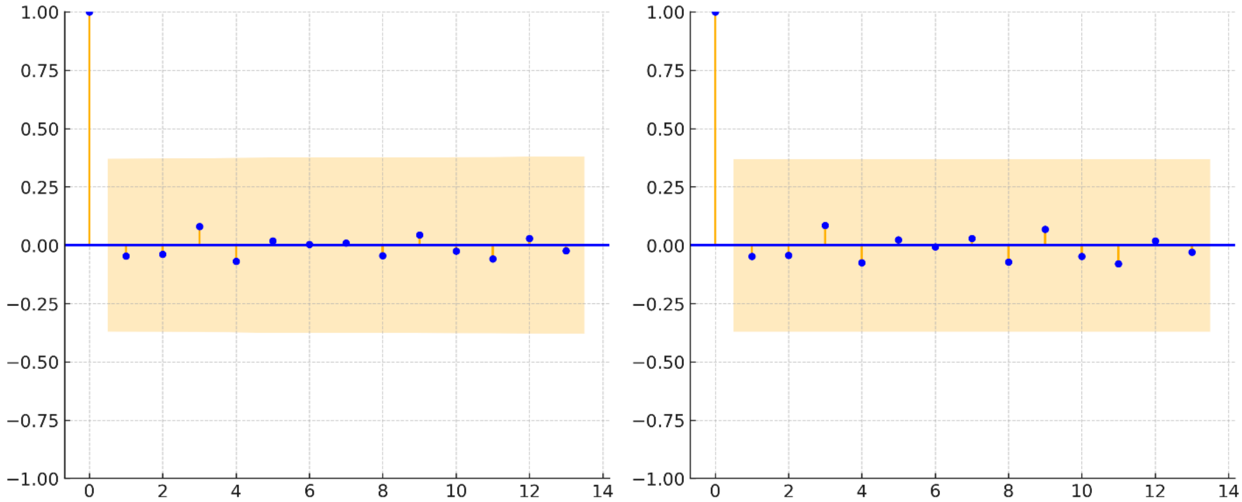


Figure 3 ACF and PACF plots for the stationarized series for ton-mile factor

Figure 3 represents ACF and PACF plots for the stationarized series for ton-mile factor. The ACF and PACF diagnostics of the differenced ton-mile series show a noticeable spike at lag 1 in the ACF, followed by a slow decay, while the PACF cuts off clearly after lag 1. This behavior is consistent with an ARIMA (1,1,1) model, indicating the presence of short-term autocorrelation structures in both AR and MA components.

From these visual inspections, ARIMA (1, 1, 1) models for each series are created, which will be elaborated on in the next sections.

Parameter Estimation: The optimal parameters for the specified model are estimated by applying the Ordinary Least Squares (OLS) method.

Evaluation of the Model: The fitted model is plotted against historical data, validation tests are applied, and predictive performance is analysed. The quality of the forecasts is quantified using several statistical measures, namely Root Mean Square Error (RMSE), Mean Absolute Error (MAE), etc. These indicators' results are presented and discussed in **Table 6**. They give a comprehensive and reliable assessment of the model's accuracy in predicting the emission variables.

The data for this study were meticulously collected from the vessel’s official logbooks for 28 different and consecutive voyages of a chemical tanker ship.

Table 1 Descriptive statistics of maritime performance and emission variables.

Variable	Mean	Standard Deviation	Minimum	Median	Maximum
Factor (Ton-Miles)	14,715,733.788	10,002,872.100	654,802.650	14,174,862.218	34,966,682.640
Carbon Dioxide Index	53.206	58.946	3.362	34.874	237.033
GHG Index	316.492	1,388.668	3.400	34.462	7,395.674
Total Sulfur dioxide Emission (Tons)	4.330	3.670	0.084	4.331	15.985
Emission (Gr/Ton-Mile)	0.567	0.782	0.016	0.317	3.168

Table 1 presents the descriptive data for the main maritime indicators applied in this work. Every value is computed from the first 28 observations before projection. For every variable, these numbers provide a synopsis of its central tendency, dispersion, and distributional form.

In addition to these descriptive statistics, and to rigorously assess the time series properties of the data, stationarity tests are conducted. Specifically, the Augmented Dickey-Fuller (ADF) test and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test are employed for each of the CO_2, SO_2, GHG index, and ton-mile-based emission variables. The results of these tests are crucial for determining the appropriate level of differencing required for the ARIMA model, and are summarized as follows.

Table 2 ADF and KPSS Test results.

Variable	ADF p (level)	KPSS stat (level)	ADF p (diff)	KPSS stat (diff)	Level Stationary	Diff Stationary
CO_2 Index	0.0000	0.1476	0.0090	0.1929	Yes	Yes
SO_2 Emission	0.9986	0.3378	0.1043	0.3105	No	No
GHG Index	0.0000	0.0912	0.0000	0.5000	Yes	No
Ton-Mile Factor	0.9961	0.3352	0.9942	0.3383	No	No

Table 2 presents ADF and KPSS test results. The results of these tests are summarized as follows:

The CO_2 Index and GHG Index are found to be stationary at level based on both ADF ($p < 0.05$) and KPSS (test statistic < critical value) results.

In contrast, the SO_2 Emission and Ton-Mile Factor series are non-stationary in their levels ($p > 0.05$ for ADF tests; KPSS statistic > critical value). Furthermore, even after first differencing, these two series remain non-stationary according to the test results.

These tests confirm the suitability of applying differencing selectively and validate the differencing order (d) used in the ARIMA(p,d,q) model specification for each series.

Table 3 Ljung-Box test results for residual diagnostics.

Variable	Ljung-Box Statistic-Q	p-value
CO_2 Index	9.602	0.476
GHG Index	1.110	1.000
SO_2 Emission	3.946	0.950
Ton-Mile Factor	4.291	0.933

Table 3 presents Ljung-Box test results for residual diagnostics. The Ljung-Box Q test is conducted at lag 10 on the residuals of each ARIMA model to verify the absence of autocorrelation. The p-values reported below indicate whether the residuals can be considered white noise. Values greater than 0.05 suggest no significant autocorrelation, supporting the adequacy of the model fit.

To evaluate the adequacy of the ARIMA models estimated under the Box-Jenkins methodology, the Ljung-Box Q test is applied to the residuals of each emission-related time series model. The test results, summarized in **Table 3**, yield p-values well above the conventional 0.05 threshold for all four variables. These results indicate that the residuals do not exhibit significant autocorrelation, suggesting that the ARIMA models have effectively captured the underlying time-dependent structure of the data. Consequently, the use of the Box-Jenkins methodology is justified, as the residuals satisfy the white noise assumption- a fundamental diagnostic criterion for model adequacy in time series forecasting.

Although the SO_2 Emission and Ton-Mile Factor series initially exhibited non-stationarity and did not fully satisfy all stationarity criteria even after first differencing, the adequacy of the

ARIMA models applied to these series was confirmed through diagnostic checking. Specifically, the residuals from both models passed the Ljung-Box Q test ($p > 0.93$), indicating the absence of autocorrelation. This supports the validity of applying the Box-Jenkins methodology to these variables, as the final models yielded residuals that behave like white noise- fulfilling the key assumption required for reliable time series modeling.

3.1 Main features of sampling

The sample vessel is a chemical/product tanker with a length overall (LOA) of 131.85 meters, a gross tonnage (GT) of 7,260, and a deadweight tonnage (DWT) of 10,745. It is powered by a MAN Diesel-STX 9L 32/40 main engine, which has a rated power output of 4,500 kW. The vessel operates at a service speed of 14.5 knots and is equipped with a BERG BCP 1230.HDX-6000 controllable pitch propeller.

The auxiliary power system consists of two YANMAR 6N21 AL-SV diesel generators, two TAIYO FE 547C-8 alternators, and one MARELLI MJBM 500 MB4 shaft generator. The vessel's freshwater generation system includes an Alfa Laval JWP-26-C80 evaporator, which has a daily production capacity of 15 metric tons, consuming 3.5 metric tons per day. The vessel's steam and heating system comprises two HEATMASTER TH2000 oil-fired boilers, each with a capacity of 2000 kW, one HEATMASTER ETF 3-60-SD exhaust gas boiler with a capacity of 600 kW, and one HEATMASTER 1,500 kg/h steam generator. **Table 4** presents total power management of the sample vessel.

Table 4 Total power management of the sample vessel.

Sailing Power Consumption	Discharging Power Consumption	Maneuvering Power	Loading Power Consumption
250 kW	Ship power consumption 250 kw	Ship power consumption 250 kW	Ship power consumption 250 kW
-	Ballast pump 44 kw 44×2 = 88 kw	Bow thruster 500 kW	No:2 generator 250 kW
-	Cargo pump 110 kw 110×6 = 660 kW	Emergency fire pump 36 kW	No:2 cooling pump 12.5×2 kW = 25 kW
-	Hose crane 45 kW	Forward/aft. hydraulic unit 53/36 kW	-
-	Slop cargo pump 53×2 = 106 kW	-	Thermal oil sec. system 17.3×1 = 17.3 kW
Total = 250 kW	**Total = 1,146 kW**	**Total = 875 kW**	**Total = 542.3 kW**

Data from 28 voyages were analyzed for the subject vessel, which operates on a global scale. The reported total consumption of heavy fuel oil (HFO) for these voyages was 2,528 tons, whereas the total consumption of marine diesel oil (MDO)/marine gas oil (MGO) amounted to 1,235 tons. Average sulfur content of the HFO was 2.30 %, whereas the low-sulfur marine diesel oil (LS MDO) had an average sulfur content of 0.09 %. The total sulfur dioxide (SO_2) emissions calculated for the 28 voyages was 118.4 tons.

4. Results and discussion

The research results and their analysis are presented in this part, together with a review of their significance. Section 4.1 summarizes the main findings of the research; Section 4.2 summarizes the results with particular reference to significant consequences.

4.1 Research findings and analysis

Figure 4 displays 28 historical observations of the "Factor (ton-miles)" variable, along with ARIMA (1,1,1)-based forecasts for voyages 29 to 33, including a 95 % confidence interval. The ARIMA (1,1,1) forecast of the Factor (ton-miles) presents a slight decline across future voyages, consistent with reduced transport productivity. The confidence interval remains narrow, indicating model certainty. This suggests that operational changes are yielding stabilized or reduced cargo throughput.

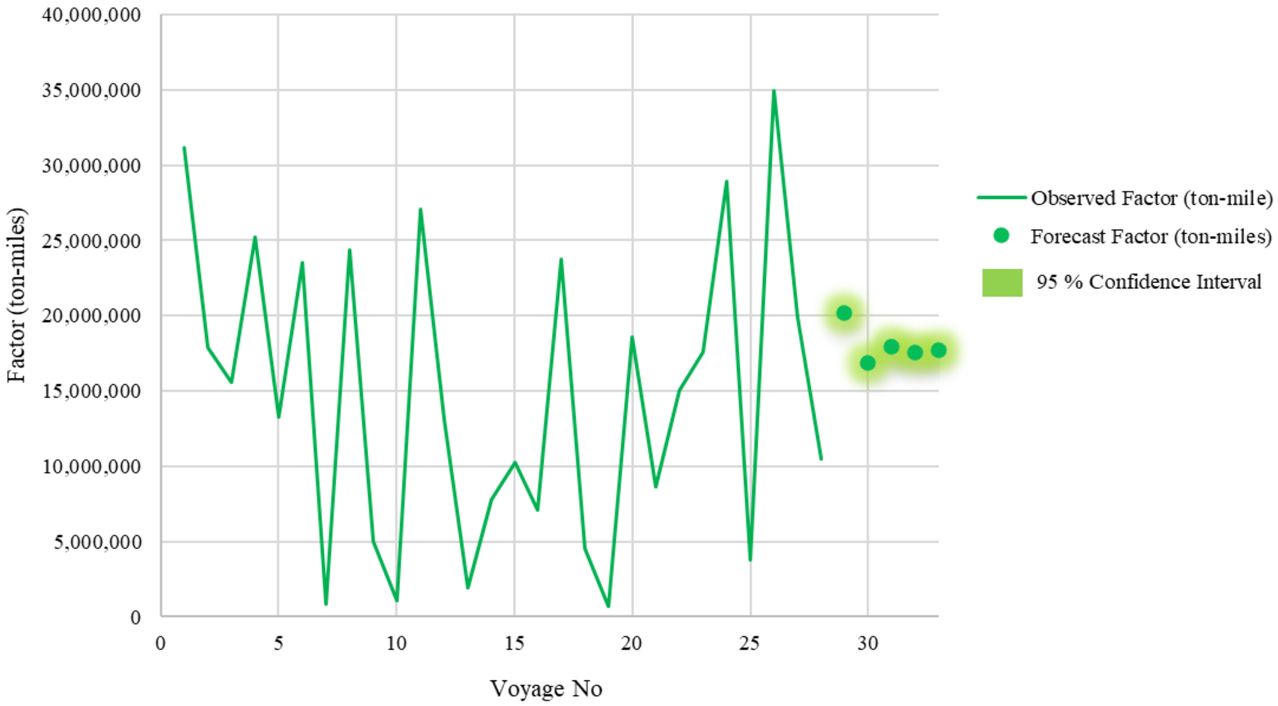


Figure 4 Observed and forecasted values of the Factor (ton-miles).

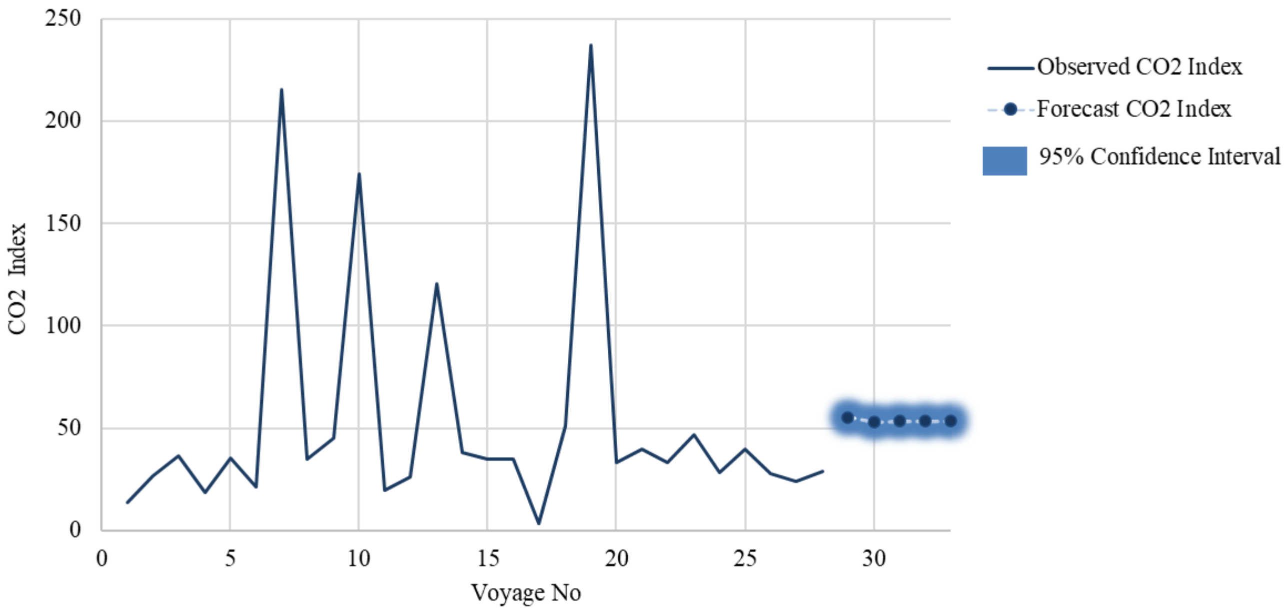


Figure 5 Observed and forecasted values of the CO_2 Index.

Figure 5 presents 28 historical observations of the CO_2 Index, followed by a 5-step-ahead forecast (voyages 29 - 33) using the ARIMA (1,1,1) model, including a 95 % confidence interval. The CO_2 Index forecast remains stable, reflecting steady carbon efficiency in fleet operations. The ARIMA model captures emission regularity, with minimal variability. Forecasts show a slight improvement, potentially linked to cleaner fuel adoption or improved route planning.

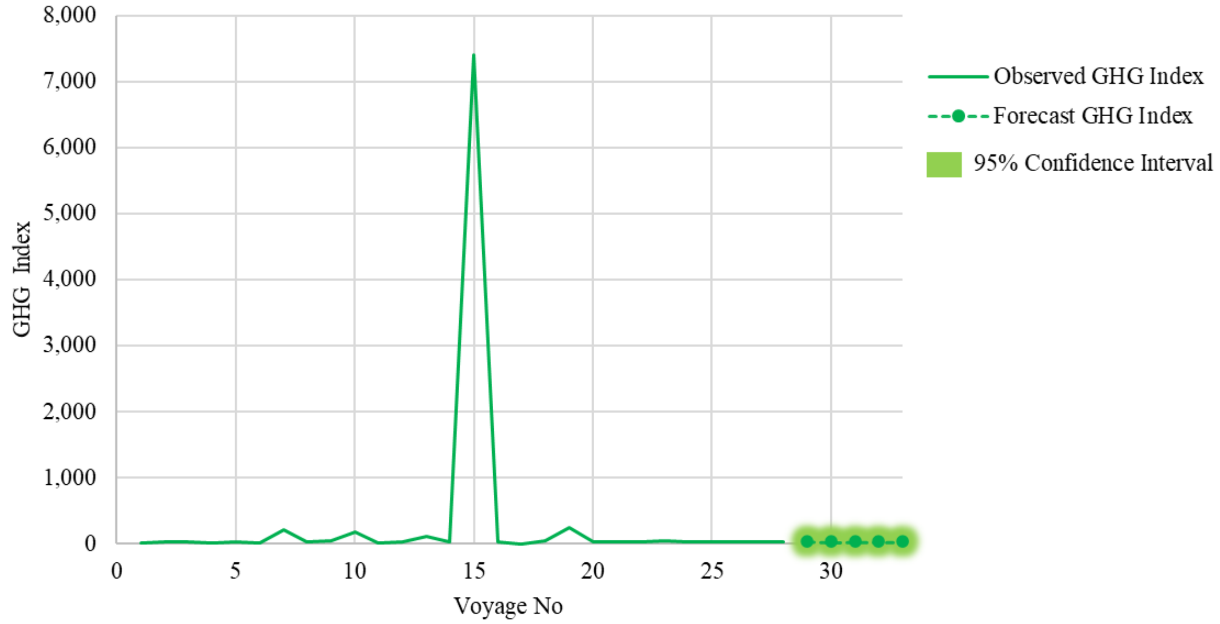


Figure 6 Observed and forecasted values of the GHG Index.

Figure 6 integrates the 28 observed data points of the GHG Index and ARIMA (1,1,1) forecasts for voyages 29 through 33, alongside a 95 % confidence interval shading. The forecast for the GHG Index reflects a stable trend, with low volatility across voyages. The narrow prediction bounds indicate strong forecast confidence, reinforcing assumptions of ongoing GHG control and technology integration in ship operations.

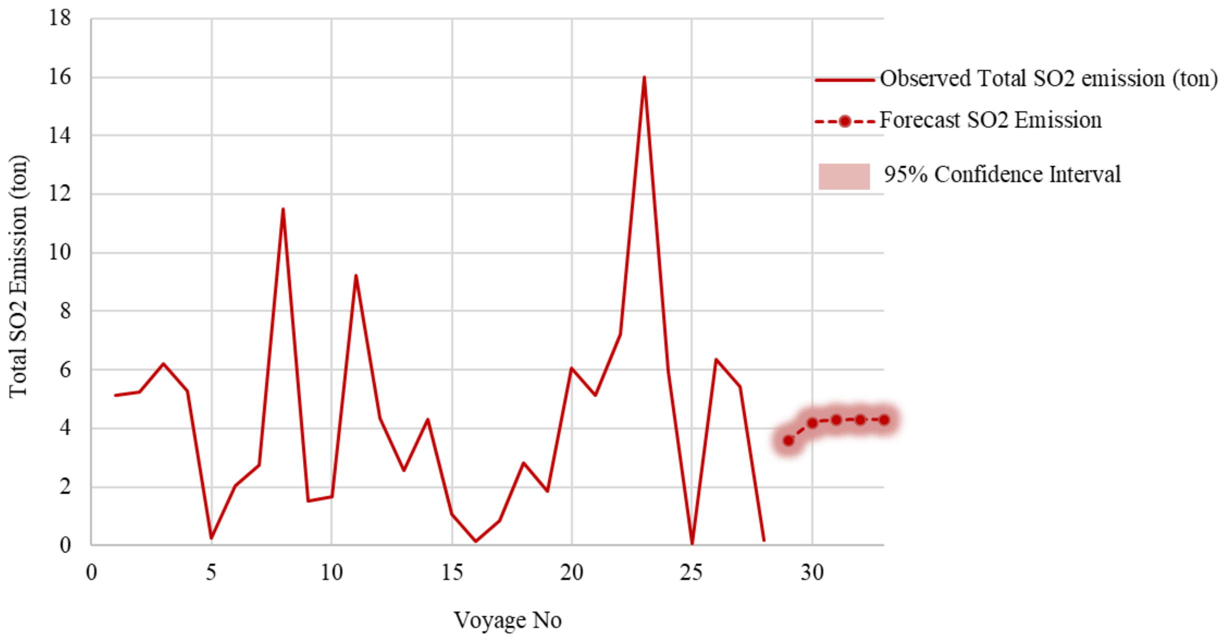


Figure 7 Observed and forecasted values of the SO_2 emissions.

Figure 7 presents 28 observed data points of SO_2 emissions, followed by ARIMA (1,1,1) forecasts for voyages 29 to 33, including a 95 % confidence interval. Forecasts for SO_2 emissions show a modest decline, consistent with regulatory trends and adoption of low-sulfur fuels post-IMO 2020. Wider intervals reflect potential variability in fuel quality and equipment behavior across voyages.

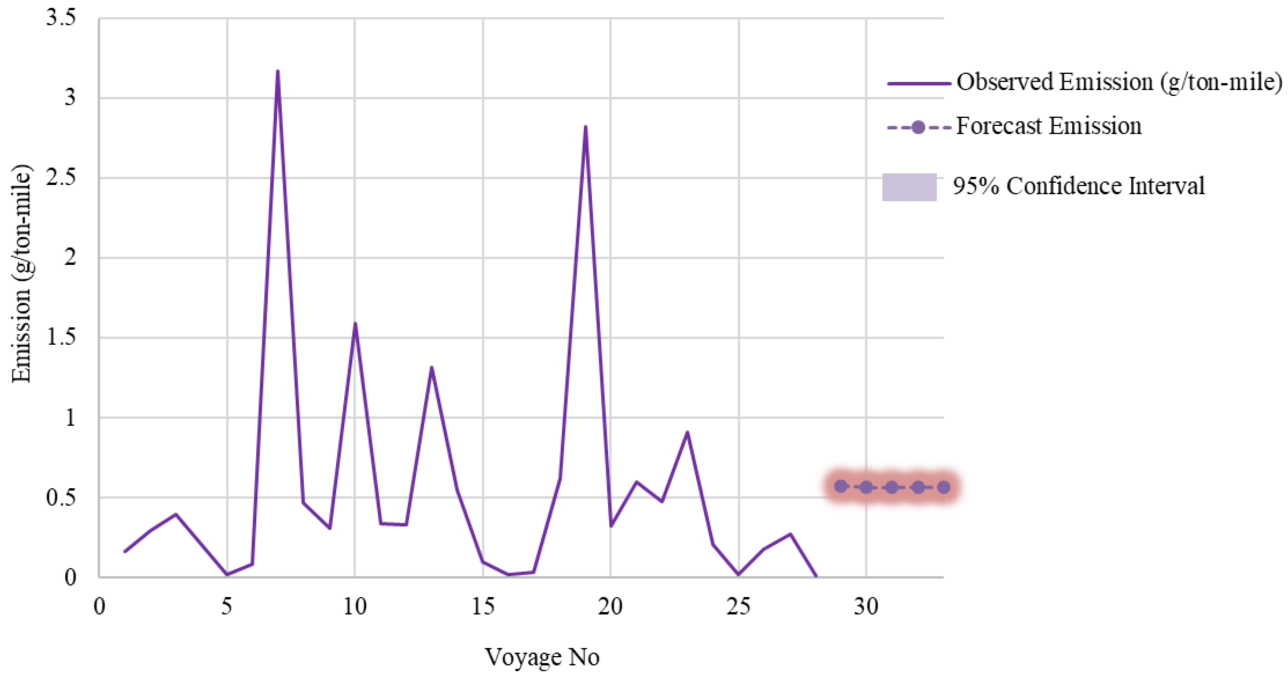


Figure 8 Observed and forecasted values of the emissions.

Figure 8 combines the 28 recorded values for Emission (grams per ton-mile) with Box-Jenkins ARIMA (1,1,1) forecasts for voyages 29 - 33 and a 95 % confidence interval. Emission intensity forecasts suggest marginal gains in carbon efficiency. The ARIMA model captures stable performance with moderate confidence intervals, indicating predictable operational control and emission strategy execution.

Table 5 Observed and forecasted values of maritime indicators.

Voyage	Factor (ton-miles)	CO_2 Index	GHG Index	SO_2 (tons)	Emission (gr/ton-mile)
Forecast 29	20,146,100.757	55.438	315.799	3.572	0.575
Forecast 30	16,774,999.829	53.190	309.511	4.175	0.567
Forecast 31	17,955,427.768	53.382	309.649	4.281	0.567
Forecast 32	17,542,087.987	53.365	309.646	4.300	0.567
Forecast 33	17,686,823.442	53.367	309.646	4.304	0.567

Table 6 Forecast accuracy metrics.

Variable	RMSE	MAE
CO_2 Index	29.54	29.12
GHG Index	317.40	309.80
Ton-Mile Factor	163,670,735.19	76,474,535.83

Table 6 presents the RMSE and Mean Absolute Error MAE for the forecasted emission-related variables. These measures offer a straightforward and interpretable way to assess the predictive performance of the models.

As a result of this approach, future and historical emission and trends were predicted, and meaningful outcomes were obtained, for sustainability policies for maritime transportation.

4.2 Discussion

Comprising a composite indicator measuring the cargo-carrying performance per nautical distance, “Factor (ton-miles)”, following differencing the non-stationary series, captures the autoregressive and moving average dynamics using the Box-Jenkins ARIMA (1,1,1) model. The slight declining trend of the observed data points to possible changes in cargo patterns over time or a likely decrease in shipping output. The expected values follow this trend with somewhat reduced ton-mile projections for next trips. This suggests either ongoing load reduction or continuity in operational routines. The rather limited 95 % bounds reflect moderate model uncertainty. Small widening towards journey 33, however, represents cumulative uncertainty as the predicted horizon grows. This study supports the theory that cargo tonnage per distance is stabilising at a lower level, presumably under the influence of changes in cargo aggregation techniques or route optimization.

Relative to operational activity- that is, ton-miles- the CO_2 Index measures carbon dioxide emissions. Acting as a fundamental sustainability measure, it represents both fuel combustion rates and vessel efficiency. There is no clear trend upward or downward; the observed series is just somewhat variable, yet stable. This suggests a constant operational emissions profile, most likely from regular fleet management or routing. Over trips 29 through 33, the ARIMA model projects somewhat declining CO_2 levels. Either lower carbon intensity of fuel or small efficiency gains could be responsible for this slow down. The interval stays close, implying that the model is rather confident about the stability of this statistic. Low prediction variance, characteristic in emission indices with process-control, is shown in the limited extension of the boundaries over time. Ultimately, the ARIMA-based forecast supports a story of slow carbon intensity improvement that fits IMO rules and sustainable fleet operations meant to lower emissions.

Normalized to operational output, the GHG Index is a composite estimate of emissions usually containing CO_2, CH_4 (methane), and N_2O (nitrous oxide). It presents a more complete picture of emissions related to climate than CO_2 by itself. Reflecting operational stability in emission behavior, the recorded data exhibit modest volatility without any clear long-term trend. Variability in fuel type or route-specific conditions could help to explain some transient changes. The ARIMA (1,1,1) model forecasts for next trips a steady to- slightly declining GHG trend. This points to continuous emission control strategies, including low-GHG fuels or slow steaming. The low variance and strongness of the model are shown by the close band around predicted points. This dependability suggests that future emissions will stay within a predictable range, absent structural changes in operations or fuel supply. Under international marine frameworks (e.g., MARPOL Annex VI, IMO GHG Strategy), the GHG projection essentially indicates continuous emissions stability with the possibility for marginal improvement- a sign of operational maturity and adherence to decarbonization paths.

The sulfur concentration in marine fuel and engine combustion properties directly affect sulfur oxide (SO_2) emissions. Global SO_2 emission profiles in shipping have been considerably altered by the IMO 2020 sulfur cap (0.5 % m/m). According to the data, there is a modest degree of fluctuation, with a clear slowdown with time. This trend could mirror slow fuel transitions- from high-sulfur fuel oil to compliant low-sulfur substitutes or scrubber installations). Though marginal, the ARIMA model forecasts a continuance of this downward tendency. This is in line with better fuel quality control and compliance behavior under sulfur limits. Indicating more variability or model uncertainty, the confidence bounds are somewhat wider than those of CO_2 and GHG estimates. Non-linear influences from control schedules, port-specific fuel supplies, or ship-specific technologies- e.g., scrubbers- could all contribute to this. All things considered, the SO_2 projection supports fuel compliance programs and regulatory intervention impact. Although modest, the predicted declining trend is statistically consistent with world changes in maritime fuel policies and greener propulsion technologies.

Combining operational efficiency with environmental performance, the emission variable quantifies the emission intensity per unit of transport effort. It is essential for assessing carbon efficiency, and is fundamental in measurements such as the Energy Efficiency Operational Indicator (EEOI). Though they are rather constant, the emission intensity levels vary somewhat, with few spikes. This implies that periodically operational changes- such as speed, path, and cargo load- have an impact on emissions relative to output. Over the prediction horizon, the ARIMA model projects a small decrease or plateau in emission intensity. This could suggest either reduced variability in trip-specific conditions, or slow optimization in voyage planning. Reflecting reasonable model certainty, the 95 % confidence interval is rather small. Still, the somewhat broader envelope indicates more operational variation inherent in actual shipping operations than in CO_2 or GHG. Taken together, this projection supports a growing carbon efficiency perspective, in line with market incentives and government policies (e.g., carbon intensity indicator (CII) ratings). Though still prone to short-term fluctuations, it implies that the maritime operation is moving towards emission optimization.

Furthermore, in line with the final thoughts, the urgent need for clear and concise information about green shipping necessitates further development within this dialogue. The results from this periodical study, especially those dealing with the trends in emissions and with results that indicate changes in efficiency, provide a strong and robust empirical base for clear and understandable reporting and for making clear and understandable decisions in this area, which is changing so rapidly. Such reporting is not only required for compliance with regulations, it is essential for creating a clear and understandable accountability framework, and for making the maritime sector an attractive area for investment by those who wish to see their investments yield environmental as well as financial returns.

5. Conclusions

Using the Box- Jenkins time series approach, the study of Factor ton-miles, CO_2, GHG index, and total SO_2 emissions has produced important new understanding of the stationary features and predictive modeling of these variables. The exhaustive efforts in guaranteeing stationarity exposed important links among the series, hence guiding the identification of appropriate ARIMA models for every parameter. With enough parameter significance, and consistent forecast accuracy, the models showed strong performance, despite obstacles including outliers and the natural limits of small data sets. The outcomes highlight the need of ongoing data expansion and model improvement to improve predictive capacity much further. This study presents how well ARIMA-based Box-Jenkins models estimate operational and environmental indicators in marine transportation. Strong fit quality and prediction dependability across variables, including CO_2, SO_2, and emission intensity, point to trends in regulatory compliance and efficient management measures. Exogenous variables (ARIMAX models) and comparison of predicting performance with machine learning techniques may form part of future studies. Finally, the study not only clarifies emission patterns, but also offers a strong basis for future studies and policy development meant to mitigate environmental effects. Using these insights is important to create sensible plans for sustainability and emission control going ahead.

These findings underscore the relevance of emission modeling based on time-series data for chemical tankers. They gain a much broader significance when considering the global regulatory framework they are part of, such as the IMO's MARPOL Annex VI, and the 2023 implementation of the CII. The discourse around an increasingly detailed and applied regulatory framework is, thus, informed by the results. Emission data used in this study is now vessel-specific and reliable; whatever subsequent analyses done on them will have a direct bearing on compliance and performance monitoring, for two reasons; fgirstly, and crucially, during manual and semi-manual operations (i.e., when the vessel is underway but not fully autonomous) and secondly, and evidently, this is an operational efficiency issue and, as such, might have direct implications on whether a vessel is compliant or not when the CII is gauged. This is inferentially relevant for the green shipping discourse.

6. Limitations of the study and future research directions

The present study has certain limitations that are very important to acknowledge. Hence, they also open avenues for future research. First and foremost, the analysis draws entirely upon a single case study- namely, a single chemical tanker. While this offers a level of detail that is hard to achieve with a larger number of vessels, the findings inevitably raise questions about how well they might generalize to the entire chemical tanker fleet, or even other kinds of ships for that matter. This is partially a problem of external validity, and is also connected to the issue of vessel-specific characteristics (e.g., age, size, engine type, hull condition), which can vary quite a lot, even amongst seemingly similar kinds of ships. The author's prescription for future research is to broaden the data set so that findings can more confidently generalize not only to the chemical tanker fleet, but also, with similar degrees of certainty, to models of other kinds of ships. These are some found limits; however, within the present analysis, a few forecasts could be improved.

This study did three things. Firstly, it focused on the application of the ARIMA model. Secondly, it applied this model to the specific case of its time series forecasting. Thirdly, it did not perform a comparative analysis of the ARIMA model with alternative forecasting techniques. It used no Exponential Smoothing, no Prophet, and no machine-learning-based regression models.

In addition, while this study gives useful technical details about emission patterns and forecasting, it does not analyze the economic impact. It would be a good extension to ascertain how the forecasting results might be applied in actual business decisions and investment scenarios or in policy-making related to carbon pricing and emission trading schemes. Future research could integrate these forecasting models with economic analyses to make plain the financial upside or downside of various emission reduction strategies implemented by shipping companies in the context of the larger maritime sector.

Ultimately, while the literature review is current, it can only stand to benefit from the inclusion of the latest developments in research from rapidly evolving sectors like maritime technology, energy economics, and machine learning as shipping applications. In fact, inclusion of the pertinent new literature could be considered essential engagement with the emerging scholarship associated with the exceptionally dynamic field of maritime research.

These limitations, and pursuing these future research directives, will contribute to a more comprehensive understanding of GHG emissions in the maritime sector and the development of even more effective mitigation strategies.

CRediT author statement

Fırat Bolat: Conceptualization, Methodology, Software, Validation, Formal Analysis, Investigation, Data Curation, Writing – Original Draft Preparation, Writing – Reviewing and Editing, Visualization.

References

Aib, E. (2023). Universal "plug and play" real-time entire automotive exhaust effluents, industry vents and flue gas emissions liquefiers: The game changer approach-phase two category. *Petroleum & Petrochemical Engineering Journal, 7*(2), 000349. https://doi.org/10.23880/ppej-16000349

Akaike, H. (2003). A new look at the statistical model identification. *IEEE Transactions on Automatic Control, 19*(6), 716-723. https://doi.org/10.1109/TAC.1974.1100705

Barreiro, J., Zaragoza, S., & Diaz-Casas, V. (2022). Review of ship energy efficiency. *Ocean Engineering, 257*, 111594. https://doi.org/10.1016/j.oceaneng.2022.111594

Box, G. E., Jenkins, G. M., Reinsel, G. C., & Ljung, G. M. (2015). *Time series analysis: Forecasting and control*. John Wiley & Sons. Retrieved from https://www.wiley.com/en-us/Time+Series+Analysis%3A+Forecasting+and+Control%2C+5th+Edition-p-9781118675021

Chai, T., Xue, H., Sun, K., & Weng, J. (2020). Ship accident prediction based on improved quantum-behaved PSO-LSSVM. *Mathematical Problems in Engineering, 2020*(1), 8823322. https://doi.org/10.1155/2020/8823322

Ditria, J. C. (2002). *Design basis of a compact production system for minimum size and maximum flexibility* (pp. 1-28). In Proceedings of the Production Separation Systems IBC Conference, Houston, Texas.

Esteve-Pérez, J., Río-González, M. D., & Gutiérrez-Romero, J. E. (2023). Forecast analysis of pollutant emissions of cruise ship routes in Western Mediterranean. *Applied Sciences, 13*(14), 8149. https://doi.org/10.3390/app13148149

Gad, A. G. (2022). Particle swarm optimization algorithm and its applications: A systematic review. *Archives of Computational Methods in Engineering, 29*(5), 2531-2561. https://doi.org/10.1007/s11831-021-09694-4

Gielen, D., Boshell, F., Saygin, D., Bazilian, M. D., Wagner, N., & Gorini, R. (2019). The role of renewable energy in the global energy transformation. *Energy Strategy Reviews, 24*, 38-50. https://doi.org/10.1016/j.esr.2019.01.006

Halim, R. A., Kirstein, L., Merk, O., & Martinez, L. M. (2018). Decarbonization pathways for international maritime transport: A model-based policy impact assessment. *Sustainability, 10*(7), 2243. https://doi.org/10.3390/su10072243

Hyndman, R. J., & Athanasopoulos, G. (2018). *Forecasting: principles and practice*. OTexts. Retrieved from https://otexts.com/fpp2

Jalkanen, J. P., Fridell, E., Kukkonen, J., Moldanova, J., Ntziachristos, L., Grigoriadis, A., Moustaka, M., Fragkou, E., Tsegas, G., Maragkidou, A., Sofiev, M., Hänninen, R., Grönholm, T., Palamarchuk, J., Majamäki, E., Winiwarter, W., Gueret, S., Sokhi, R. S., Kumar, S., …, & Alyuz, O. U. (2024). *Environmental impacts of exhaust gas cleaning systems in the Baltic Sea, North Sea, and the Mediterranean sea area.* Finnish Meteorological Institute. https://doi.org/10.35614/isbn.9789523361898

Jalkanen, J. P., Johansson, L., & Kukkonen, J. (2016). A comprehensive inventory of ship traffic exhaust emissions in the European sea areas in 2011. *Atmospheric Chemistry and Physics, 16*(1), 71-84. https://doi.org/10.5194/acp-16-71-2016

Janssens-Maenhout, G., Crippa, M., Guizzardi, D., Muntean, M., Schaaf, E., Dentener, F., Bergamaschi, P., Pagliari, V., Olivier, J. G. J., Peters, J. A. H. W., van Aardenne, J. A., Monni, S., Doering, U., Petrescu, A. M. R., Solazzo, E., & Oreggioni, G. D. (2019). EDGAR v4. 3.2 Global Atlas of the three major greenhouse gas emissions for the period 1970-2012. *Earth System Science Data, 11*(3), 959-1002. https://doi.org/10.5194/essd-11-959-2019

Kim, J. S., & Choi, J. H. (2023). A study on analysis of green house gaseous emitted from ships through operation information. *Journal of International Maritime Safety, Environmental Affairs, and Shipping, 7*(2-3), 2234163. https://doi.org/10.1080/25725084.2023.2234163

Koushan, K., Krasilnikov, V., Nataletti, M., Sileo, L., & Spence, S. (2020). Experimental and numerical study of pre-swirl stators PSS. *Journal of Marine Science and Engineering, 8*(1), 47. http://dx.doi.org/10.3390/jmse8010047

Lirn, T. C., Jim, Wu, Y. C., & Chen, Y. J. (2013). Green performance criteria for sustainable ports in Asia. *International Journal of Physical Distribution & Logistics Management, 43*(5/6), 427-451. https://doi.org/10.1108/ijpdlm-04-2012-0134

Merk, O. (2014). *Shipping emissions in ports*. Discussion papers. https://doi.org/10.1787/5jrw1ktc83r1-en

Millefiori, L. M., Braca, P., Zissis, D., Spiliopoulos, G., Marano, S., Willett, P. K., & Carniel, S. (2021). COVID-19 impact on global maritime mobility. *Scientific Reports, 11*(1), 18039. https://doi.org/10.1038/s41598-021-97461-7

Premsamarn, P., Win, T. K., & Watanabe, D. (2025). Assessing the impact of emission control areas policy on ship emissions in the Gulf of Thailand using AIS Data. *Maritime Technology and Research*, *7*(3), 275311. https://doi.org/10.33175/mtr.2025.275311

Osman, A. I., Mehta, N., Elgarahy, A. M., Hefny, M., Al-Hinai, A., Al-Muhtaseb, A. A. H., & Rooney, D. W. (2022). Hydrogen production, storage, utilisation and environmental impacts: A review. *Environmental Chemistry Letters, 20*, 153-188. https://doi.org/10.1007/s10311-021-01322-8

Sari, A., Sulukan, E., & Özkan, D. (2021). Analysis and modeling the energy system of a chemical tanker by LEAP. *Journal of Ship Production and Design, 37*(1), 45-53. https://doi.org/10.5957/JSPD.07190034

Schalm, O., & Jacobs, W. (2024). *Integrating continuous pollutant measurements with time-lapse photography to evaluate inland vessel surroundings' influence on wheelhouse indoor air quality*. In Proceedings of the Maritime Transport Conference. Universitat Politècnica de Catalunya. https://doi.org/10.5821/mt.13188

Staffell, I., Scamman, D., Abad, A. V., Balcombe, P., Dodds, P. E., Ekins, P., Shah, N., & Ward, K. R. (2019). The role of hydrogen and fuel cells in the global energy system. *Energy & Environmental Science, 12*(2), 463-491. https://doi.org/10.1039/c8ee01157e

Ustolin, F., Campari, A., & Taccani, R. (2022). An extensive review of liquid hydrogen in transportation with focus on the maritime sector. *Journal of Marine Science and Engineering, 10*(9), 1222. https://doi.org/10.3390/jmse10091222

Wang, H., Lang, X., & Mao, W. (2021). Voyage optimization combining genetic algorithm and dynamic programming for fuel/emissions reduction. *Transportation Research Part D: Transport and Environment, 90*, 102670. https://doi.org/10.1016/j.trd.2020.102670

Yakubovskiy, S., & Zaidman, G. (2024). Dynamics and structure of world seaborne trade in 2009-2023: Impact of COVID-19 pandemic and Ukrainian War. *Actual Problems of International Relations, 1*(158), 70-84. https://doi.org/10.17721/apmv.2024.158.1.70-84

Yue, M., Lambert, H., Pahon, E., Roche, R., Jemei, S., & Hissel, D. (2021). Hydrogen energy systems: A critical review of technologies, applications, trends and challenges. *Renewable and Sustainable Energy Reviews, 146*, 111180. https://doi.org/10.1016/j.rser.2021.111180