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Predictive modelling in the shipping industry: analysis from supply and demand sides

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Abstract

Purpose – Maritime transportation plays an important role in facilitating both the global and regional merchandise trade, where accurate trend prediction is crucial in assisting decision-making in the industry. This paper aims to conduct a macro-level study to predict world vessel supply and demand.

Design/methodology/approach – The automatic autoregressive integrated moving average (ARIMA) is used for the univariate vessel supply and demand time-series forecasting based on the data records from 1980 to 2021.

Findings – For the future projection of the demand side, the predicted outcomes for total vessel demand and world dry cargo vessel demand until 2030 indicate upward trends. For the supply side, the predominant upward trends for world total vessel supply, oil tanker vessel supply, container vessel supply and other types of vessel supply are captured. The world bulk carrier vessel supply prediction results indicate an initial upward trend, followed by a slight decline, while the forecasted world general cargo vessel supply values remain relatively stable. By comparing the predicted percentage change rates, there is a gradual convergence between demand and supply change rates in the near future. We also find that the impact of the COVID-19 pandemic on the time-series prediction results is not statistically significant.

Originality/value – The results can provide policy implications in strategic planning and operation to various stakeholders in the shipping industry for vessel building, scrapping and deployment.

Keywords Vessel supply and demand, Time-series forecasting, Automatic ARIMA model, COVID-19 impact, Policy implications

Paper type Research paper

1. Introduction

The maritime transport plays an important role in world merchandise trade, carrying approximately 80% of the volume of international trade. In addition, the maritime industry can also play a vital role in the economic system at the regional level, serving as a fundamental component for both resource importation and exportation as well as employment opportunity provision (Yan *et al.*, 2021). Trend prediction is crucial in shipping markets, as numerous efforts aim to improve forecast accuracy, aiding decision-making in the industry (Fiskin and Cerit, 2021). However, the uncertain and complex nature of this shipping industry makes predictions more difficult. Particularly, adjustments in shipping supply respond slowly to shifts in demand in the short term (Greenwood and Hanson, 2015). Although the international supply chain and logistics have faced disruptions such as port delays and container shortages due to the COVID-19 pandemic, the shipping industry has been demonstrating signs of recovery; for instance, container freight has returned to pre-pandemic levels (UNCTAD, 2023). In this case, short-term cross-correlation

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can be more pronounced compared to the long term, and the level of multifractality can be stronger following a crisis than preceding it (Chen *et al.*, 2017).

Over the recent years, significant changes in the shipping industry's supply and demand have been observed, understanding and predicting whose trends can help maritime policymakers and infrastructure planners develop pertinent legislation and action plans at the macro-level (Sou and Ong, 2016) and assist shipping companies in making informed strategic decisions regarding fleet expansion and resource allocation (Kim, 2019). The freight demand experienced significant fluctuations due to the effects of both the trade war and the COVID-19 pandemic (Huang *et al.*, 2023). In addition, the supply side of the shipping industry contends with fierce global competition and crises arising from imbalances between supply and demand (Wada *et al.*, 2022). A number of research works have analysed the supply and demand trends in the maritime industry with various focuses and contexts. Broadly, Kalgora and Christian (2016) reviewed the relevant data and information regarding the impact of the financial and economic crisis on the container ship market. Kim (2019) conducted a review of the related literature to examine the disconnection between supply and demand in the shipping market. Krikigianni *et al.* (2022) focused on the matchmaking of supply and demand needs in the maritime supply chain, where a system design framework was presented. Nevertheless, mathematical models have not been formulated systematically to support the discussions in these papers.

Thereby, this study aims to conduct a macro-level study to analyse and forecast the worldwide supply and demand for vessels. The contribution of this study is twofold: First, this research work utilises time-series prediction models to analyse the supply and demand trends in the shipping industry by cargo and vessel types. The percentage changes between vessel supply and demand are also compared and contrasted. Second, this study analysed the impact of the COVID-19 pandemic on the predictive models of vessel supply and demand. The findings of this paper can provide policy implications for various stakeholders in the shipping industry, such as planners and shipping companies.

The remainder of this paper is organised as follows: Section 2 reviews the related works. Section 3 elaborates on the data for analysis. Section 4 illustrates the research methodology for predictive modelling, i.e. the automatic autoregressive integrated moving average (ARIMA) model. Section 5 presents and discusses the results of this paper. Lastly, Section 6 concludes this paper and outlines the potential directions for future research.

2. Related work

In this section, we review the related works to this paper from two aspects, namely shipping industry supply and demand analysis and time series forecasting models in maritime industry.

2.1 Supply and demand analysis in the shipping industry

Some empirical shipping predictions focused on quantitative models using different forecasting techniques, including econometric models (Gavriilidis *et al.*, 2018), time series models (Rashed *et al.*, 2017) or soft computing techniques (Chen *et al.*, 2021). New technologies in big data and simulation provide opportunities to carriers and their shipping networks for better analytical results (Yuan *et al.*, 2020; Yap *et al.*, 2023). Sourced from the automatic identification system (AIS), Regli and Nomikos (2019) utilised correlating data with the whereabouts of the "free" tanker fleet in the ocean to improve the accuracy of forecasting. Chen *et al.* (2019) employed wavelet analysis to predict the long-term patterns of shipping demand and fluctuations in freight rates. Moiseev (2021) applied an exponential smoothing model on the average time-charter equivalent values to forecast the oil tanker shipping market in crisis periods.

Regarding the supply side of shipping industry, Organisation for Economic Cooperation and Development (2017) discussed the oversupply of shipbuilding capacity and assessed policy responses for governments. Sakalayen *et al.* (2021) developed a forecast model for new building orders using the multivariate ARIMA approach. Fan *et al.* (2018) indicated that market dynamics, costs and operational variables greatly influence fleet capacity supply, highlighting a trend of prudent decision-making regarding ordering new vessels and careful considerations regarding ship demolitions in the container market, largely due to the substantial capital investment involved.

To further construct the mathematical frameworks for both supply and demand analysis in the shipping industry, Martius *et al.* (2022) built machine learning and probabilistic models to predict the regional supply and demand for empty containers, i.e. the expected location of containers and the timestamp of containers' arrival in the short- or mid-term. Zhu *et al.* (2023) focused on supply and demand analysis for the trade route "China–Singapore International Land-Sea Trade Corridor (C-S-ILSTC)" and the implications for trade and transportation between China and the Association of Southeast Asian Nations (ASEAN) region, where the demand side is the trade volume and the commonly traded cargo types between China and ASEAN, and the supply side is the infrastructure and essential nodes along C-S-ILSTC. Similar to this study, the ARIMA model was used for time series prediction. Nevertheless, while Zhu *et al.* (2023) predominantly focused on demand and supply analysis for the C-S-ILSTC, this study conducts a broader analysis of demand and supply trends in the shipping industry overall. In addition to the aforementioned research works, there are other related studies; for instance, Nomikos and Tsouknidis (2023) and Park *et al.* (2023) investigated the supply and demand shocks in the general shipping freight market and the dry bulk shipping market, respectively.

2.2 Time series prediction in the maritime industry

In the maritime industry, time series prediction has been conducted by researchers to forecast a variety of critical factors. As mentioned in Section 2.1, time series prediction models such as ARIMA have been commonly utilised for shipping supply and demand analysis. In addition, to facilitate port operation and management, the prediction of container throughput at ports was also well studied, where methods such as recurrent neural networks (RNN), convolutional neural networks (CNN) and ARIMA were adopted (Tan *et al.*, 2021; Jin *et al.*, 2021; Munim *et al.*, 2023). In particular, a number of researchers applied the seasonal autoregressive integrated moving average (SARIMA) model to provide a seasonal forecast of container throughput at ports (Farhan and Ong, 2018; Koyuncu *et al.*, 2021; Mokhtar *et al.*, 2022).

Besides, real-time maritime traffic prediction was also investigated by researchers based on both time series data and geo-spatial data to better understand vessel motion patterns and improve the efficiency and safety of maritime traffic (Bodunov *et al.*, 2018; Ramin *et al.*, 2020; Rong *et al.*, 2022). Similarly, for maritime accident prediction, researchers commonly utilise geo-spatial data together with time series data for forecasting purposes (Sui *et al.*, 2023; Nourmohammadi *et al.*, 2023). As maritime accident occurrence should be associated with multiple accident contributing factors, Wang *et al.* (2023) proposed a multi-factor accident prediction framework based on an autoregressive integrated moving average with explanatory variables (ARIMAX) model. Additionally, freight cost forecasting has also attracted the attention of numerous researchers; for example, Yang and Mehmed (2019) utilised artificial neural network (ANN) models to predict shipping freight rates. Munim and

Schramm (2021) conducted a comparative study to predict the container freight rates of major trade routes.

In general, despite the abundant research in the realm of supply and demand analysis and time series forecasting in the maritime industry, the existing research has distinct aims and contexts at a relatively micro level. This research investigates the trends and patterns of supply and demand in the shipping industry from a macro level, where the impact of the COVID-19 pandemic has also been taken into consideration.

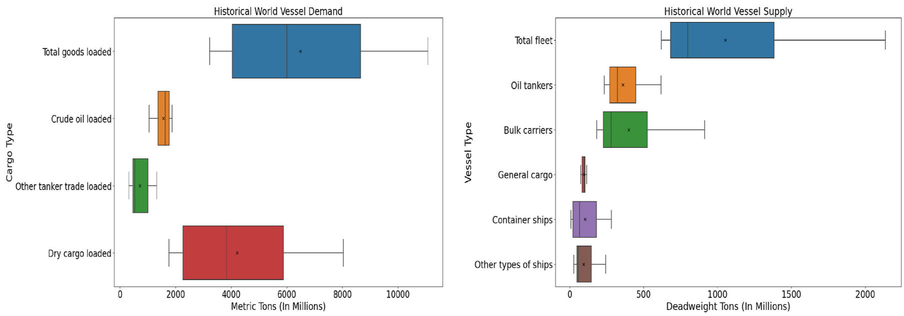
3. Data

In this paper, we extract and utilise the world vessel supply and demand data from the United Nations Conference on Trade and Development statistics database (UNCTADstat, 2023). In particular, the annual merchant fleet data by type of ship is used for supply analysis, and the annual world seaborne trade data by type of cargo is used for demand analysis. As of the time this study is conducted, the available supply and demand data extend up to the 2022 and 2021, respectively. To synchronise the supply and demand data for the same timeframe, we utilised the data records from 1980 to 2021. Note that the seaborne transportation demand is a derived demand, which can be affected by numerous factors such as the world economy (Kim, 2019). Nevertheless, for the demand analysis of this study, due to the data availability concern, we utilise the observed demand data, i.e. the actual cargo load carried by vessels.

The descriptive statistics of historical world vessel supply and demand is summarised in Figure 1, where the total goods loaded and total fleet are also included in Figure 1(a) and (b) to provide a visual benchmark for comparing against other cargo and vessel types, respectively. Within the study period, the demand based on dry cargo loaded in metric tons is significantly higher than that of crude oil and other tanker trade. For the vessel supply, which is measured by deadweight tons, the supply oil tankers and bulk carriers generally exceeds that of general cargo vessels, container ships and other types of vessels.

4. Methodology

In this section, we elaborate on the predictive model formulation for supply and demand analysis in the shipping industry. In particular, the ARIMA model is applied for univariate supply and demand time series data forecasting, where the future supply and demand values



Demand distribution by vessel types

(a)

Supply distribution by vessel types

(b)

Figure 1. Descriptive statistics

Source(s): Figure by authors

are predicted based on a linear combination of their respective past values and errors, as shown in Eq. (1):

$$\phi(B)\left(1 - B^d\right)Z_t = \theta(B)\epsilon_t, \quad (1)$$

where Z_t represents the supply or demand value in the shipping industry at year t; ϵ_t denotes the white noise series, whose mean value is zero and B denotes the backward shift operator, which satisfies Eq. (2).

$$B^n Z_t = Z_{t-n} \quad (2)$$

To tune the ARIMA model, three parameters are typically to be considered, namely p that indicates the number of autoregressive terms, q that indicates the number of moving average terms and d that denotes the difference in order. In Eq. (1), $\phi(B)$ and $\theta(B)$ are polynomials of order p and q, respectively. A toy example of the ARIMA model is included here for illustration purposes. When $p = 1$, d = 0, q = 0, the ARIMA model is a simple first-order autoregressive model, such that the model utilises the lagged value of the time series at one step back (Z_{t-1}) to predict the current value Z_t. The time series is stationary as $d = 0$ and the model does not utilise the past forecasted errors to predict Z_t as q = 0.

More details on the deduction process of the ARIMA model are available in Hyndman and Khandakar (2008). The automatic ARIMA model utilised in this study follows an iterative method while adhering to the order constraints, and the best ARIMA model is selected based on the root mean square error (RMSE) value.

5. Results and discussion

5.1 Parameter configuration and model performance

As stated in Section 4, three parameters p, d and q are tuned to optimise the shipping industry supply and demand predictive models. For each of the supply and demand datasets, we split it into an 80% training set for parameter tuning and model development, and a 20% test set to evaluate model performance. The automatic ARIMA model adjusts the values of parameters p, d and q within the ranges of (0,8), (0,2) and (0,8), respectively, where the optimal (p, d, q) set corresponding to each predictive model is summarised in Table 1. In addition to the RMSE value, the percentage error (PE) value is also provided in the table to express the RMSE as a percentage of the mean observed value. Note that as mentioned in Section 3, since we are using the observed demand data, for the remainder of the paper, we refer to "total goods

Table 1. ARIMA model parameter settings and results

	ARIMA model	p, d, q	RMSE (train)	RMSE (test)	PE (train)	PE (test)
Demand	World total vessel	4, 1, 0	218.12	483.05	3.94%	4.57%
	World crude oil vessel	3, 1, 5	76.58	78.12	5.09%	4.35%
	World dry cargo vessel	3, 1, 3	154.67	405.31	4.50%	5.37%
	World other tanker trade vessel	6, 1, 1	65.55	66.70	11.05%	5.39%
Supply	World total vessel	7, 0, 5	40.64	154.57	4.77%	8.10%
	World oil tanker vessel	7, 1, 2	26.75	50.82	8.47%	9.31%
	World bulk carrier vessel	6, 0, 1	19.42	61.57	6.45%	7.54%
	World general cargo vessel	0, 1, 2	2.21	0.93	2.18%	1.21%
	World container vessel	2, 1, 3	2.54	22.67	3.70%	9.01%
	World other types of vessel	4, 1, 0	7.09	20.16	10.89%	9.24%

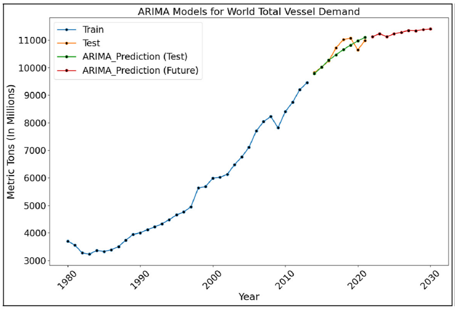
Source(s): Table by authors

loaded" in Figure 1(a) as "world total vessel demand", "crude oil loaded" as "world crude oil vessel demand", "dry cargo loaded" as "world dry cargo vessel demand" and "other tanker loaded" as "world other tanker trade vessel demand".

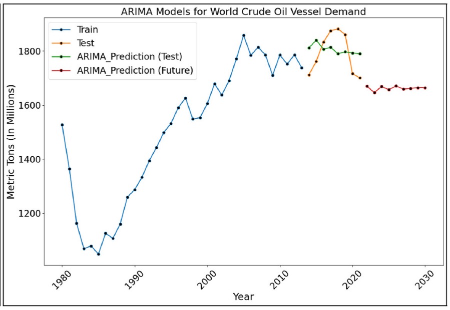
Observing Table 1, the models' performance is generally acceptable, whereas we found that the two general prediction models for the demand and supply of "world total vessel" perform worse than the specific prediction models for vessel demand by cargo types and supply models by vessel type, respectively, in terms of RMSE. The result could be attributed to the heterogeneity in the vessel demand and supply datasets, which is captured by the specific models more effectively. In terms of the PE values, the results implicate that the models fitness across different cargo and vessel types with various scales are generally comparable.

5.2 Temporal analysis of forecasted trends

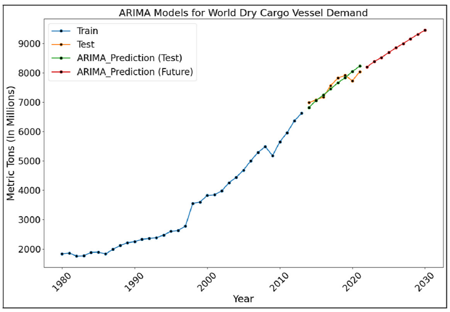
Figure 2 demonstrates the world demand trends by different vessel and/or cargo types, where the legends "Train" and "Test" indicate the actual values, while the "ARIMA_Prediction (Test)" and "ARIMA_Prediction (Future)" indicate the predicted values. During the training and testing phases, the prediction models have successfully captured the general upward trend for world total vessel demand, world dry cargo vessel demand and world other tanker trade vessel demand, as demonstrated in Figure 2(a, c–d). For the future projection, the predicted outcomes until 2030 also indicate upward trends. On the other hand, the world



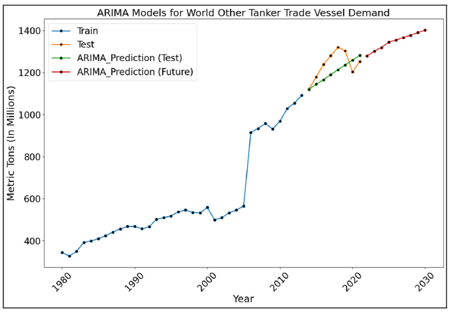
World Total Vessel Demand
(a)



World Crude Oil Vessel Demand
(b)



World Dry Cargo Vessel Demand
(c)



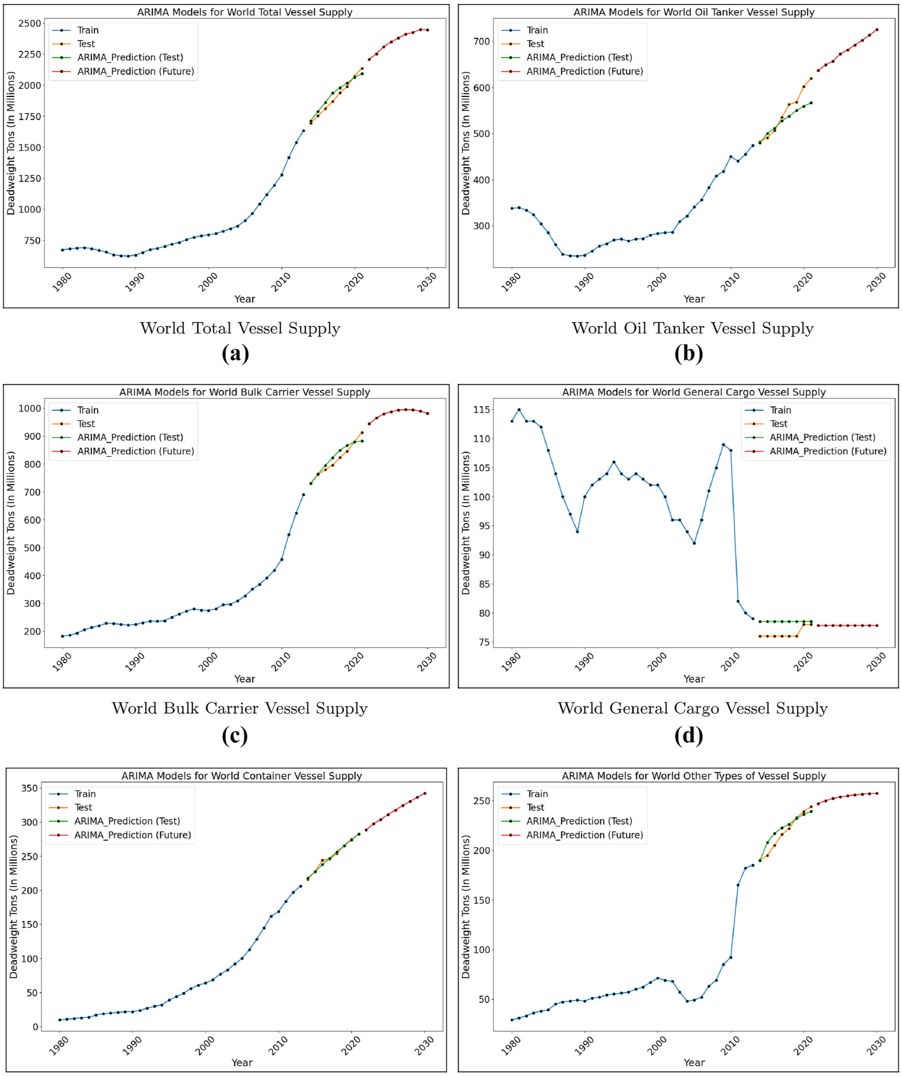
World Other Tanker Trade Vessel Demand
(d)

Source(s): Figure by authors

Figure 2.
Demand trends

crude oil vessel demand has been fluctuating throughout the training period (as shown in Figure 2(b), such that the predicted trend on the test set for the recent years does not closely match the actual demand very well. Nevertheless, the RMSE of the model (as shown in Table 1) indicates that the overall accuracy of the predictions is still acceptable, and the future projection also indicates fluctuations.

On the other hand, the world supply trends by different vessel types are depicted in Figure 3. In both the training and testing phases, the predominant upward trends have also



World Total Vessel Supply
(a)

World Oil Tanker Vessel Supply
(b)

World Bulk Carrier Vessel Supply
(c)

World General Cargo Vessel Supply
(d)

World Container Vessel Supply
(e)

World Other Types of Vessel Supply
(f)

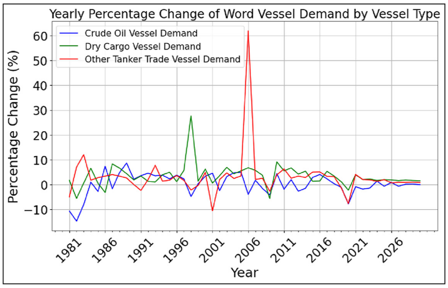
Source(s): Figure by authors

Figure 3.
Supply trends

been captured by the predictive models for world total vessel supply, oil tanker vessel supply, container vessel supply and other types of vessel supply, as demonstrated in Figure 3(a, b, e–f), respectively. Similarly, the projected results suggest upward trends regarding the future forecast until 2030. For the world bulk carrier vessel supply prediction in Figure 3(c), the predicted outcomes suggested an initial upward trend followed by a slight decline. Lastly, Figure 3(d) shows that the actual world general cargo vessel supply has been generally decreasing over the study period since 1980; hence, the forecasted supply values remain relatively stable until 2030.

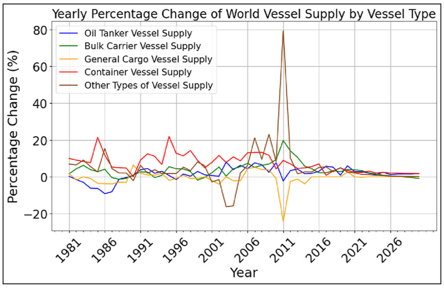
5.3 Percentage change of supply and demand

The vessel supply and demand data are measured and recorded in different units, which makes it challenging to directly compare their trends. Therefore, we derive the percentage change of vessel supply and demand throughout the study period to facilitate meaningful comparative analysis, as shown in Figure 4. Accordingly to Figure 4(a), a significant increase in demand for other tanker trade vessel has occurred around the year 2006, followed by a downturn due to the Great Recession spanning from 2007 to 2009. A similar downturn is observed for the year 2020, which can be explained by the economic downturn brought on by the COVID-19 pandemic. On the other hand, a significant increase in the world vessels supply for bulk carrier vessel and other types of vessels has been observed



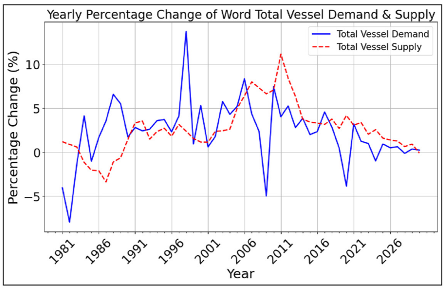
Percentage change in demand

(a)



Percentage change in supply

(b)



Percentage change in total

(c)

Source(s): Figure by authors

Figure 4.
Percentage change of supply and demand

based on Figure 4(b), which can be explained by the deliveries of new buildings (UNCTAD, 2011).

Overall, the percentage changes by world total vessel supply and demand are summarised in Figure 4(c), where notable declines in vessel demand in the years 2009 and 2020, as well as a peak in supply in 2011, have been observed. Based on the time series models' prediction results, there could be a gradual convergence between demand and supply in the near future.

5.4 COVID-19 impact analysis

The COVID-19 pandemic had a significant impact on the maritime industry (Yazir *et al.*, 2020); hence, we would also like to investigate whether the pandemic has a significant impact on the time series prediction results of vessel supply and demand. Thereby, in this section, we further compare the RMSE of the time series prediction model with and without consideration of the years during the COVID-19 pandemic. $RMSE_{incl}$ represents RMSE results from the ARIMA model built on the full dataset from 1980–2021 for analysis, as shown in Section 5.1. $RMSE_{excl}$ indicates the results from the ARIMA models that exclude years from 2020 onwards, reflecting the global impact of COVID-19 starting in that year, as shown in Table 2.

Based on the RMSE results, we conduct an independent two-sample two-tailed t-test based on the null hypothesis that the means of $RMSE_{incl}$ and $RMSE_{excl}$ are equal, whose p-value results are summarised in Table 3. It is observed that the p-value associated with the t-test is not statistically significant at the commonly accepted significance level of 0.05. Therefore, we do not have enough evidence to reject the null hypothesis. In other words, we have found that the impact of the COVID-19 pandemic on our time series predictions for vessel supply and demand is not statistically significant.

Table 2. ARIMA model (excluding COVID-19 pandemic) parameter settings and results

	ARIMA model	p, d, q	RMSE (train)	RMSE (test)
Demand	World total vessel	4, 1, 2	157.77	701.01
	World crude oil vessel	3, 1, 2	53.53	65.46
	World dry cargo vessel	2, 1, 7	115.8	549.84
	World other tanker trade vessel	7, 1, 3	54.41	101.61
Supply	World total vessel	0, 1, 5	62.27	154.02
	World oil tanker vessel	7, 1, 5	53.21	41.88
	World bulk carrier vessel	0, 1, 6	44.45	72.91
	World general cargo vessel	3, 1, 7	5.35	1.64
	World container vessel	6, 0, 1	2.79	24.36
	World other types of vessel	0, 1, 4	21.3	12.63

Source(s): Table by authors

Table 3. t-test result of COVID-19 impact

Dataset	Supply	Demand
Train	0.4760	0.6359
Test	0.2393	0.9867

Source(s): Table by authors

6. Conclusions

Maritime transportation plays a crucial role in facilitating both the global and regional merchandise trade. This study aims to conduct a macro-level study to forecast world vessel supply and demand, where the automatic ARIMA is used for the univariate vessel supply and demand time series prediction. For the future projection results the demand side, upward trends are indicated for total vessel demand, dry cargo vessel demand and other tanker trade vessel demand until 2030. For the supply side, the predominant upward trends for world total vessel supply, oil tanker vessel supply, container vessel supply and other types of vessel supply are also captured by the predictive model. The world bulk carrier vessel supply prediction indicates an initial upward trend, followed by a slight decline, while the forecasted world general cargo vessel supply remains relatively stable. By comparing the predicted percentage change rates, a gradual convergence between demand and supply change rates is observed for the near future. The impact of the COVID-19 pandemic on the time series prediction results is not found to be statistically significant.

The results can provide policy implications in strategic planning (vessel building and scrapping) and operation (vessel deployment) in the shipping industry; for example, shipping companies can consider reducing certain vessel types to focus on others that are needed to meet the forecasted demand. This paper is limited to the temporal analysis of vessel supply and demand. In future research, spatial analysis of the forecasted trends can be further conducted to provide a more comprehensive view of the supply and demand trends in the shipping industry. In addition, micro-level studies can be further conducted to investigate the supply and demand conditions within specific economies or zones of the shipping industry. A more advanced time series prediction model can also be further utilised, subject to data availability.

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