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# Passenger traffic in Polish seaports in the face of the COVID-19 pandemic

**Sebastian Sobczuk**[1]✉**, Anna Borucka**[2]

[1] https://orcid.org/0000-0002-2969-5606
[2] https://orcid.org/0000-0002-7892-9640

Military University of Technology, [1]Doctoral School, [2]Faculty of Security, Logistics and Management
2B Kaliskiego St., 00-908 Warsaw, Poland
e-mail: [1]sebastian.sobczuk@wat.edu.pl, [2]anna.borucka@wat.edu.pl
✉ corresponding author

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**Abstract**

The outbreak of the COVID-19 pandemic had a profound impact on the global economy and disrupted daily life across many regions of the world. Restrictions imposed at the time, such as the closure of national borders and restrictions on mobility, led to unprecedented challenges for the transportation sector and related tourism services compared with any prior crisis. This disruption also affected maritime passenger transport in Poland. This article aims to assess the impact of the COVID-19 pandemic on passenger traffic in Polish seaports and to develop mathematical models that could support management in the event of future epidemic threats. Three different models are proposed, which showed that the epidemic crisis resulted in a significant decline in passenger traffic at Polish seaports. The most accurate proved to be the SARIMA model. The Holt-Winters model also demonstrated high fitting and predictive performance. In turn, the STL model offered intriguing insights with its time series decomposition, enabling a detailed analysis of individual components. A comparative analysis of the proposed models confirms their usefulness in forecasting passenger traffic in seaports in the face of disruptions such as the COVID-19 pandemic. These models can be an effective decision-support tool, helping to reduce the negative effects of future epidemic threats.

## Introduction

Threats such as pandemics, geopolitical conflicts, climate change, and terrorist attacks significantly influence the modern world and global economy. The COVID-19 pandemic outbreak in 2020, for example, dramatically and unexpectedly affected social and economic systems, causing widespread destabilization across nearly all sectors (Clemente-Suárez, 2021). Maritime transport, essential for global passenger and cargo movement, was also impacted by the coronavirus. In response to the global epidemic crisis, shipping lines and operators had to adjust their operations to fit a new reality (Chua et al., 2022). Strict restrictions and health guidelines were imposed to curb the spreading of the virus and enhance public safety. Governments enforced widespread lockdowns and mandated social distancing and personal protective measures. Travel became more challenging due to temporary border closures, increased border checks, and mandatory quarantines upon entry into countries (Sobczuk, 2024). These restrictions, along with evolving legal regulations and new safety standards, affected the operational performance and transport outcomes. In the face of a dynamically changing situation, passenger maritime transport in Poland has faced the challenge of adapting to restrictions and new operating standards. The lack of appropriate analyses may make it difficult to understand the real scale of the problem and limit the sector's adaptive capacity, especially from the perspective of a potential recurrence of similar events. Therefore, this study aims to assess the impact of the COVID-19 pandemic on passenger traffic in Polish seaports and to develop mathematical models that can support management in the event of future epidemic threats. This study not only showed the scale of disruptions caused by COVID-19 in passenger traffic in Polish seaports but, above all, provides effective forecasting tools for the maritime transport sector, which can be used for operational and strategic planning in the face of potential epidemic threats. This will enable a more effective response to similar challenges in the future, which will consequently reduce the negative effects of crisis events such as pandemics.

## Literature review

In recent years, maritime transport in Poland has seen consistent growth. Port facilities have been modernized, and infrastructure has been expanded and enhanced through modern technologies. These investments aimed to increase cargo volumes and improve passenger comfort. As a result, the importance of maritime transport grew, leading to an increase in both passenger numbers and cargo volumes (Bocheński et al., 2021). However, this positive trend was disrupted by the outbreak of the COVID-19 pandemic in 2020. The pandemic led to a decrease in demand for transport services, port closures, and extended waiting times for port operations (such as docking and cargo handling) due to expanded security checks. Business and corporate travel were either postponed or replaced by virtual meetings for safety reasons. Tourists, constrained by mobility restrictions in most countries, opted for domestic travel, often using personal transportation. This shift was evident in transport statistics, particularly for summer cruises. The pandemic also led to rising freight and charter rates in container transport. Additionally, decreased demand for and prices of oil resulted in reduced deliveries, necessitating the storage of oil on floating tankers. These disruptions contributed to rising insolvencies and even bankruptcies among maritime carriers (Cullinane & Haralambides, 2021; Węcel et al., 2024).

Numerous publications have examined maritime transport during the COVID-19 pandemic. These studies analyze the operational activities of carriers and assess the measures taken to mitigate the negative impacts of reduced revenues from passenger transport and ferry services (Urbanyi-Popiolek, 2020). Another study explored the crisis's implications for the future of European maritime transport and proposes directions for further development (van Tatenhove, 2021). There have also been analyses of the impact of the pandemic on cargo maritime transport based on vessel types and the evaluations of cargo throughput in ports (Borucka & Kozlowski, 2023). Additionally, the need to reconfigure global supply chains managed by container transport and enhance their resilience through new digital solutions has been emphasized (Grzelakowski, 2022). The system of maritime navigation, with a focus on passenger traffic and trends within the European Union, has also been studied (Gracan, 2022). Some studies have visualized the impact of the COVID-19 pandemic on maritime transport in Poland and developed long-term forecasts for passenger traffic (Barczak, 2023). Nevertheless, there is a noticeable lack of focus on mathematical models that can evaluate and forecast passenger traffic in Polish seaports amid the pandemic's disruptions, which is the primary focus of this publication.

## Materials and methods

This study utilized quarterly data on the passenger numbers to and from Polish seaports from 2004 to 2024, provided by Eurostat, to construct the time series necessary for the analysis (Eurostat, 2024).

Time series models were employed to identify and forecast temporal changes, allowing for the description of the process under study, the detection of the deterministic components, and the representation of the process as a function containing components such as the trend, seasonal variations, cyclical fluctuations, and random variations (Borucka & Guzanek, 2022; Bouboulas et al., 2022; Oszczypala et al., 2023). By identifying these components and the internal dynamics of the time series, future values of the time series can be forecast (Rodrigues et al., 2022; Kozlowski et al., 2023). Three different models were applied in this study, and their results were compared (Liu et al., 2024). If observations of the lagged series appear as dependent variables in the model, it is appropriate to apply autoregressive processes AR ($p$). If the variables in the model are a combination of lagged external disturbances, moving average models are suitable MA ($q$). Often, combining these two models – i.e., ARMA ($p$,$q$) – is the most effective approach.

However, for non-stationary series that can be transformed into a stationary form (through differencing), it is appropriate to use ARIMA ($p,d,q$) models. When seasonal components are also included in the model, the SARIMA ($p,d,q$)($P,D,Q$)[S] model is obtained (Riaz et al., 2023), i.e.,

$$\begin{gathered}\left(1-\varphi_1 B-\varphi_2 B^2-\cdots-\varphi_p B^p\right)\cdot \\ \cdot\left(1-\Phi_1 B^s-\Phi_2 B^{2s}-\cdots-\Phi_P B^{Ps}\right)\cdot \\ \cdot(1-B)^d\left(1-B^s\right)^D y_t= \\ =\left(1+\theta_1 B+\theta_2 B^2+\cdots+\theta_q B^q\right)\cdot \\ \cdot\left(1+\Theta_1 B^s+\Theta_2 B^{2s}+\cdots\Theta_Q B^{Qs}\right)\varepsilon_t\end{gathered} \tag{1}$$

where $\varphi_1,\varphi_2,\ldots,\varphi_p$ is the autoregression coefficients, $\Phi_1,\Phi_2,\ldots,\Phi_P$ is the seasonal autoregression coefficients, $\theta_1,\theta_2,\ldots,\theta_q$ is the moving average coefficients, $\Theta_1,\Theta_2,\ldots,\Theta_q$ is the seasonal coefficients of the moving average, $B$ is the differentiation operator $B_{yt} = y_t - y_{t-1}$, and $\varepsilon_t$ is the random error at time $t$.

The Holt-Winters model, which is applicable to time series with trend, seasonal, and random fluctuations, was also used. There are two variants of this model that differ in the nature of the seasonal components. The additive model is preferred when seasonal variations are roughly constant across the series, while the multiplicative model is used when seasonal variations change proportionally with the series level (Koehler et al., 2001; Ribeiro et al., 2019). This study used a multiplicative model consisting of the forecasting equation $Y^*_{t+m}$ and three smoothing equations – i.e., the level $L_t$, trend $B_t$, and seasonality $S_t$ – which are expressed as

$$Y^*_{t+m}=\frac{L_t+B_t\cdot m}{S_{t-s+m}} \tag{2}$$

$$L_t=\alpha\frac{Y_t}{S_{t-s}}+(1-\alpha)\left(L_{t-1}+B_{t-1}\right) \tag{3}$$

$$B_t=\beta\left(L_t-L_{t-1}\right)+(1-\beta)B_{t-1} \tag{4}$$

$$S_t=\gamma\frac{Y_t}{L_t}+(1-\gamma)S_{t-s} \tag{5}$$

respectively, where $\alpha$, $\beta$, and $\gamma$ are the exponential smoothing coefficients such that $\alpha, \beta, \gamma_\varepsilon (0;1)$, $Y_t$ is the actual value at time $t$, $S$ is the length of the seasonality cycle (for quarterly data, $L = 4$), and $m$ is the forecast horizon (Wang, 2019).

The last model employed was the seasonal-trend decomposition using LOESS (STL), which decomposes the time series to analyze each component separately. As a result, the value of the variable under study ($Y_t$) at time $t$ is expressed as the sum of the trend, seasonal, and remainder so that:

$$Y_t = M_t + S_t + R_t \tag{6}$$

where $M_t$ is the trend at time $t$, $S_t$ is the seasonality at time $t$, and $R_t$ is the remainder component at time $t$.

The component values are determined through a series of locally weighted regression (LOESS) smoothing procedures, which are based on fitting a weighted polynomial regression to the observation time (Dagum & Luati, 2003). The time series is iteratively adjusted until the trend and seasonality stabilize using a multi-step process involving alternating moving averages and LOESS smoothing. The seasonal, trend, and remainder components are then extracted using the following equations:

$$S_t=S_t^{(k+1)} \tag{7}$$

$$M_t=M_t^{(k+1)} \tag{8}$$

$$R_t = Y_t - S_t - M_t \tag{9}$$

respectively, where $k$ is the number of iterations for the respective steps.

A model selection was based on the Akaike information criterion (AIC) and the Bayesian information criterion (BIC), which are calculated using the following formulae:

$$\text{AIC} = 2\,k - 2\ln(L) \tag{10}$$

$$\text{BIC} = k\ln(n) - 2\ln(L) \tag{11}$$

where $k$ is the number of parameters in the model, $L$ is the reliability function, and $n$ is the number of observations. Lower AIC and BIC values indicate a better model fit.

For each of the models used, the accuracy of the determined forecasts was also evaluated. Forecast accuracy for each model was assessed by calculating the mean absolute error (MAE), mean square error (MSE), and root mean square error (RMSE) via:

$$\text{MAE}=\frac{1}{n}\sum_{t=1}^{n}\left|Y_t^*-Y_t\right| \tag{12}$$

$$\text{MSE}=\sum_{t=1}^{n}\frac{\left(Y_t^*-Y_t\right)^2}{n} \tag{13}$$

$$\text{RMSE}=\sqrt{\text{MSE}}=\sqrt{\sum_{t=1}^{n}\frac{\left(Y_t^*-Y_t\right)^2}{n}} \tag{14}$$

where $Y_t^*$ is the forecasted value at time $t$, $Y_t$ is the actual value at time $t$, and $n$ is the number of observations. Lower error values indicate higher forecast accuracy and, thus, better predictive performance of the model (Saigal & Mehrotra, 2012).

In this paper, time series analyses and the development of all the mathematical models were performed using R Core software (version 4.3.3) with packages that provide a set of algorithms for data preprocessing and time series forecasting (R Core Team, 2024).

## Comparison of the mathematical models describing passenger traffic in Polish seaports

This study began with an analysis of the passenger numbers in Polish seaports using basic descriptive statistics. Data from each quarter of 2004–2023 were analyzed and displayed using a box plot, as shown in Figure 1.

Transport data from 2004–2023 were also analyzed by quarter (Q1–Q4), as illustrated in Figure 2.

The plots reveal significant variability in the passenger numbers from year to year, especially compared to 2019. Notably, 2020–2021 show distinct outliers, which are attributed to the disruptions caused by the COVID-19 pandemic, which led to temporary mobility restrictions, including maritime travel (Chua et al., 2022; Węcel et al., 2024).

Additionally, the data exhibit quarterly seasonality, with the highest passenger numbers in the third (Q3) and second (Q2) quarters. This pattern is due to favorable weather conditions for maritime travel during the spring and summer months, leading to increased cruise bookings. The third quarter's

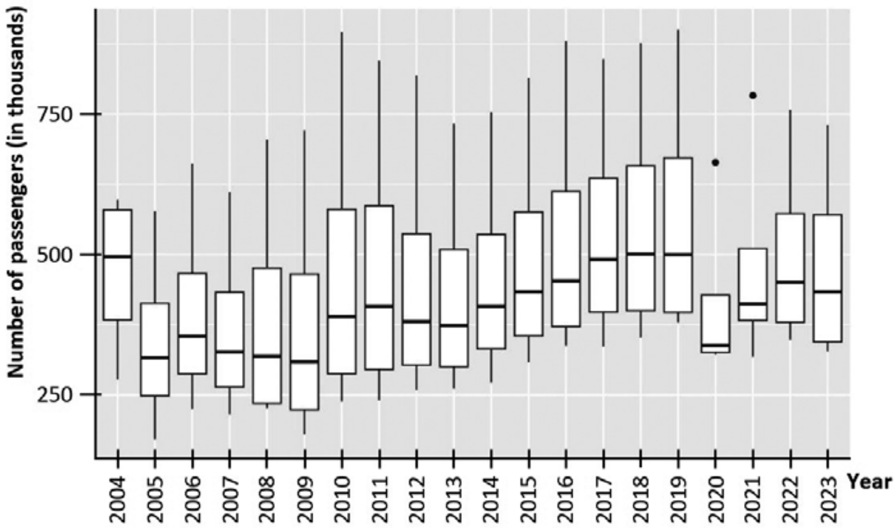


**Figure 1. Box plot of the passenger numbers in Polish seaports from 2004 to 2023 (based on Eurostat, 2024)**

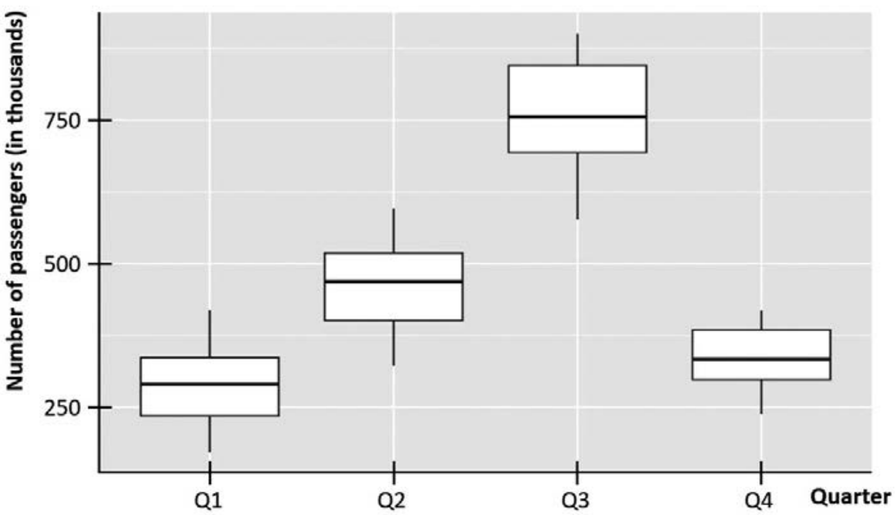


**Figure 2. Box plot of the number of passengers in Polish seaports by quarter based on data from 2004 to 2023 (based on Eurostat, 2024)**

holiday season also significantly contributes to increased passenger traffic in seaports. In the remaining parts of the year (Q1 and Q4), there are fewer passengers, primarily due to business travel and less frequent tourist trips (Gracan et al., 2022; Barczak, 2023).

Next, a time series analysis of the quarterly passenger numbers from 2004–2023 was conducted. The dataset was divided into training and testing sets, with the division occurring at the end (Q4) of 2022, as shown in Figure 3.

The SARIMA model was initially proposed. The best model, determined based on information criteria, was SARIMA (1,0,0)(0,1,1)[4]. The estimated parameter values for this model are presented in Table 1.

**Table 1. SARIMA (1,0,0)(0,1,1)[4] model parameters**

| Model parameters | | |
|---|---|---|
| Coefficients | AR 1 | SMA 1 |
| | 0.6488 | −0.3189 |
| Standard error | 0.1009 | 0.1432 |

The values of the individual information criteria (i.e., AIC and BIC) are similar and are summarized together in Table 2.

**Table 2. Evaluation of SARIMA (1,0,0)(0,1,1)[4] model fit**

| Evaluation of the model fit | |
|---|---|
| Aikike information criterion (AIC) | 791.71 |
| Bayesian information criterion (BIC) | 798.54 |

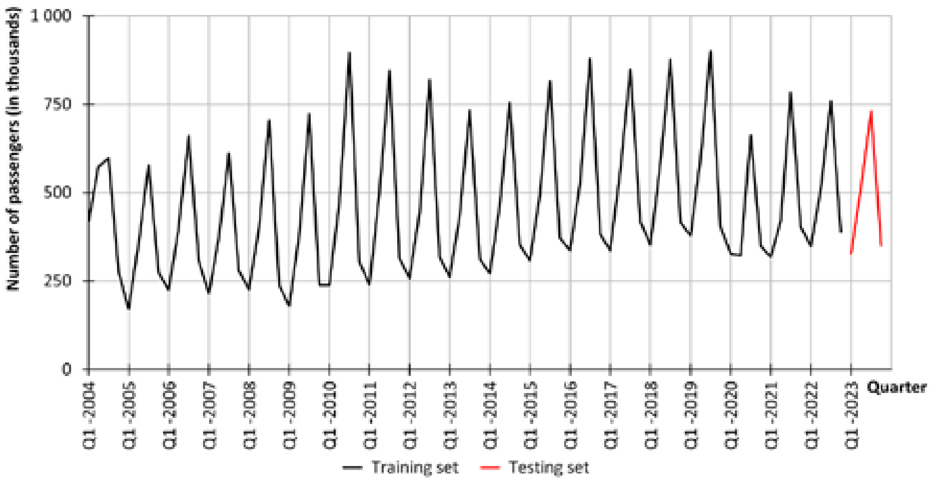


**Figure 3. Dataset division into training and testing sets (based on Eurostat, 2024)**

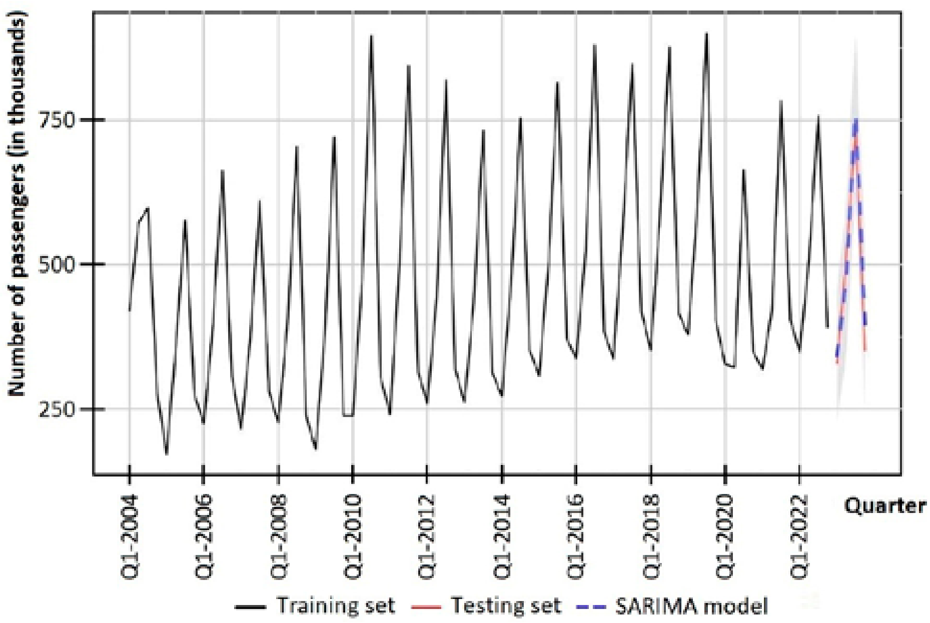


**Figure 4. Passenger numbers in Polish seaports with SARIMA (1,0,0)(0,1,1)[4] model forecast**

The MAE, RMSE, and MSE forecast errors were also determined. The results were satisfactory, with lower errors for the testing set, indicating high prediction accuracy (Table 3).

**Table 3. Forecast accuracy measures for the SARIMA (1,0,0)(0,1,1)[4] model**

| Forecast accuracy measures | | |
|---|---|---|
| | Training set | Testing set |
| MAE | 36.6301 | 29.6084 |
| RMSE | 54.8371 | 31.6947 |
| MSE | 3007.1097 | 1004.554 |

The actual passenger numbers in Polish seaports from 2004–2023, along with the forecast based on the SARIMA (1,0,0)(0,1,1)[4] model, are shown in Figure 4.

The next proposed model was the Holt-Winters model with multiplicative seasonality. The values of the smoothing parameters and initial parameters are presented in Table 4.

**Table 4. Parameters of the multiplicative Holt-Winters model**

| Model parameters | | | |
|---|---|---|---|
| Smoothing parameters | | Initial parameters | |
| Alpha ($\alpha$) | 0.3655 | l | 550.1898 |
| Beta ($\beta$) | 0.0001 | b | 0.2276 |
| Gamma ($\gamma$) | 0.6344 | s | 1.3228 |
| | | | 1.1652 |
| | | | 0.8699 |

The Holt-Winters model was also evaluated using information criteria (Table 5). The values obtained were higher than those for the SARIMA model, indicating a poorer fit than the SARIMA (1,0,0)(0,1,1)[4] model.

**Table 5. Evaluation of the multiplicative Holt-Winters model fit**

| Evaluation of the model fit | |
|---|---|
| Aikike information criterion (AIC) | 951.47 |
| Bayesian information criterion (BIC) | 972.45 |

Forecast errors for the Holt-Winters model were also determined (Table 6). The error values were satisfactory for both the training and test datasets. Moreover, for the testing set, the MAE and RMSE errors were lower than those for the SARIMA model, indicating that the forecasts from this model have smaller prediction errors.

**Table 6. Forecast accuracy measures for the multiplicative Holt-Winters model**

| Forecast accuracy measures | | |
|---|---|---|
| | Training set | Testing set |
| MAE | 38.7481 | 29.1471 |
| RMSE | 56.0513 | 27.0655 |
| MSE | 3141.7505 | 849.5518 |

The actual passenger numbers in Polish seaports from 2004 to 2023, with the 2023 forecast from the multiplicative Holt-Winters model, are shown in Figure 5.

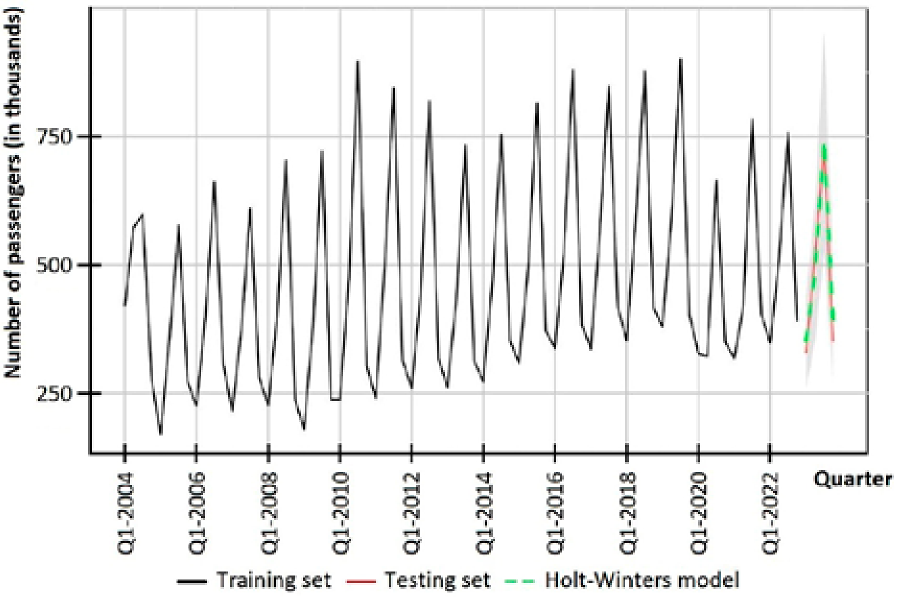


**Figure 5. Passenger numbers in Polish seaports with the multiplicative Holt-Winters model forecast**

The last model proposed is seasonal-trend decomposition using LOESS (STL), which allows for the decomposition of the time series into seasonal, trend, and remainder components. The STL model components and interquartile range (IQR) calculations are presented in Table 7.

**Table 7. STL model components with IQR calculations**

| Timeseries components | | | |
|---|---|---|---|
| | Seasonal | Trend | Remainder |
| Min. | −178.3537 | 342.6228 | −143.8509 |
| 1st Qu. | −137.745 | 397.6869 | −18.0134 |
| Median | −60.7633 | 463.6279 | −0.3256 |
| Mean | 0.00001 | 461.5133 | −0.6449 |
| 3rd Qu. | 76.9817 | 507.9549 | 19.9074 |
| Max. | 299.8803 | 582.0477 | 110.5635 |
| Inter-quartile range calculations (IQR) | | | |
| STL seasonal | STL Trend | STL remainder | Data |
| 214.73 | 110.27 | 37.92 | 274 |
| 78.4% | 40.2% | 13.8% | 100.0% |

As before, the forecast errors were also determined for the STL model, the values of which indicate high prediction accuracy (Table 8).

**Table 8. Forecast accuracy measures for the STL model**

| Forecast accuracy measures | |
|---|---|
| MAE | 28.8357 |
| RMSE | 37.1778 |
| MSE | 1382.186 |

The decomposition of the analyzed time series (Figure 6) reveals certain regularities within its components. Most notably, throughout the entire period, quarterly seasonality remains consistent, unaffected by global events such as the COVID-19 pandemic. However, when discussing disruptions, the trend line, as determined by the STL model, highlights the significant impact that the spread of the SARS-CoV-2 virus had on societal mobility, particularly on maritime passenger transport.

Analyzing the trend in passenger numbers from Q3 in 2019 to Q3 in 2020, a significant decline is evident, attributable to the epidemic crisis during that period. Therefore, considering both the seasonal component and the overall trend, it can be concluded that the COVID-19 pandemic outbreak had a substantial impact on transport outcomes, reducing passenger traffic at Polish seaports. However, it did not disrupt the established pattern of seasonal interest in cruises across different quarters.

The actual passenger numbers in Polish seaports from 2004 to 2023, along with the forecast generated using the STL model, are presented in Figure 7.

The last phase of this study involved comparing the results obtained by each of the mathematical models under consideration. Actual values were compared with forecasts for the individual quarters of 2023. The higher forecasted values, compared with the actual figures (except for Q2 2023), were obtained across all the models, which confirm that the SARS-CoV-2 pandemic significantly disrupted passenger traffic (Table 9). All the proposed models were also compared graphically with the testing set (Figure 8).

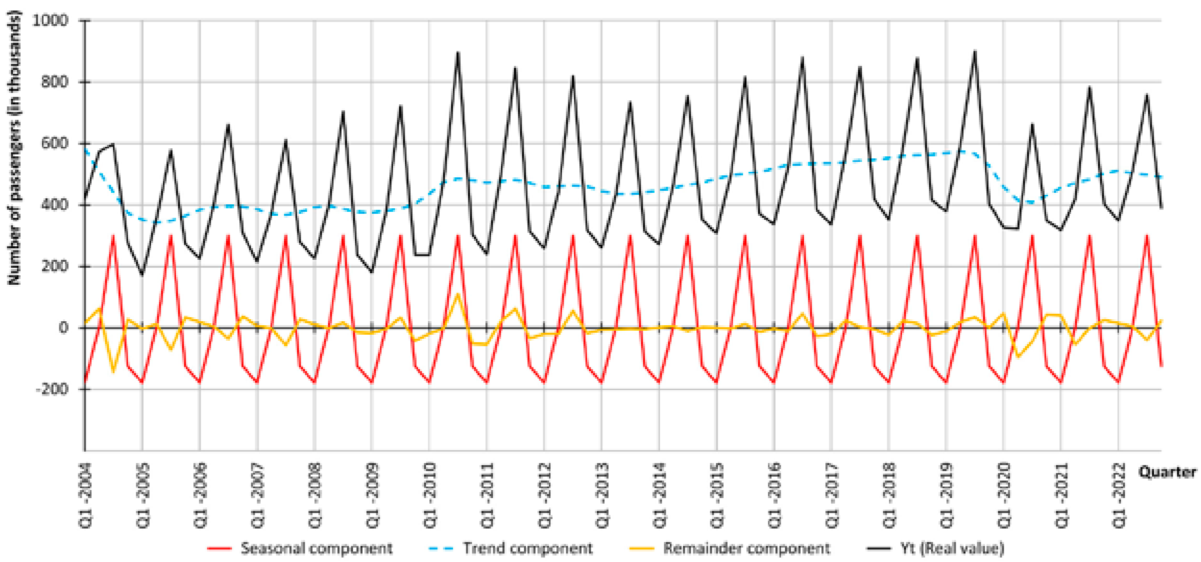


**Figure 6. Decomposition of the time series of passenger numbers in Polish seaports using the STL model**

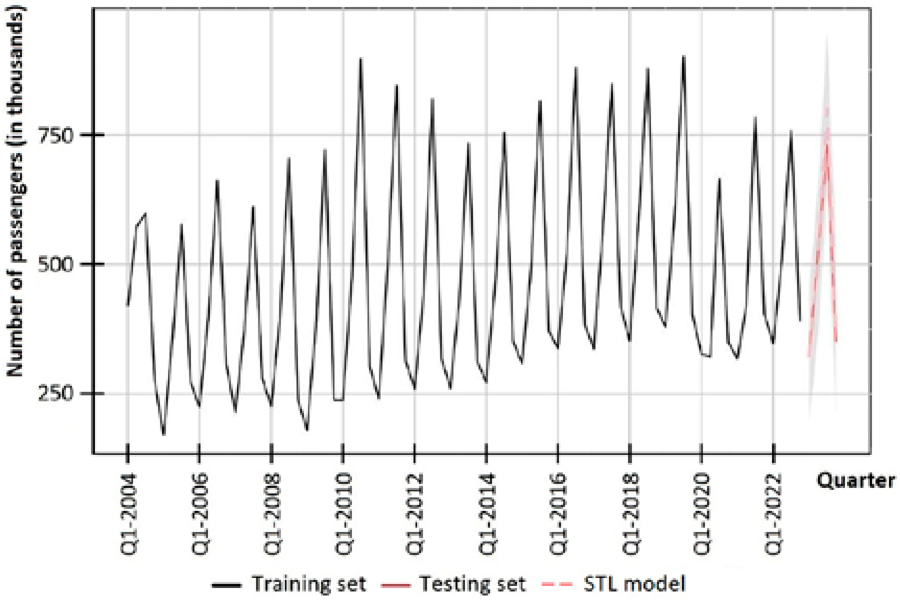


**Figure 7. Passenger numbers in Polish seaports with the STL model forecast**

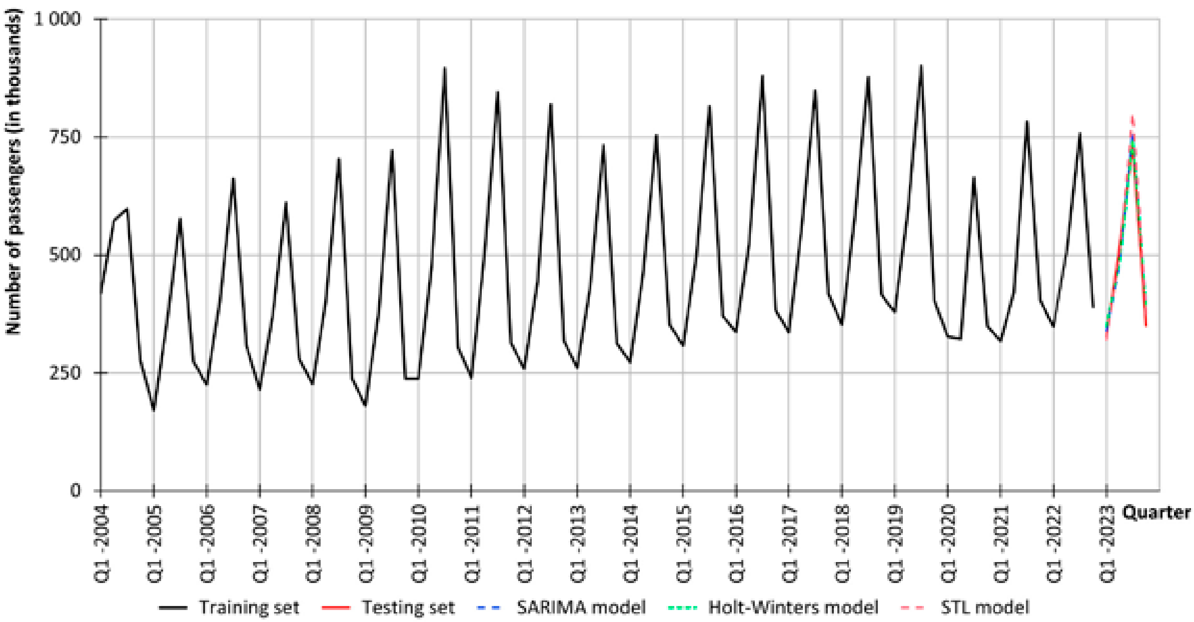


**Figure 8. Comparison of mathematical models for passenger numbers in Polish seaports**

**Table 9. Comparison of forecasts obtained by individual mathematical models**

| | Q1-2023 | Q2-2023 | Q3-2023 | Q4-2023 |
|---|---|---|---|---|
| Actual value | 328.00 | 517.00 | 731.00 | 350.00 |
| SAIRMA model | 339.23 | 479.71 | 760.60 | 390.32 |
| Holt-Winters model | 348.66 | 483.61 | 744.20 | 391.02 |
| STL model | 320.77 | 501.81 | 799.00 | 374.92 |

The results indicate that the SARIMA model provided forecasts closest to the actual values. Satisfactory results were also achieved with the multiplicative Holt-Winters model, while the STL model showed the lowest accuracy, particularly for the forecast of Q3 in 2023. Nevertheless, each proposed model offers valuable and effective tools for forecasting passenger traffic in Polish seaports, even amid global disruptions such as the COVID-19 pandemic.

## Conclusions

The impact of the COVID-19 pandemic on maritime transport was evident globally. In passenger transport, the disruptions were primarily linked to restrictions imposed, including those regarding mobility, resulting in a decrease in cruise passengers. The aim of this study, which was to assess the impact of the COVID-19 pandemic on passenger traffic in Polish seaports and to develop mathematical models that could support management in the event of future epidemic threats, has been achieved. This publication provides an evaluation of passenger traffic in Polish ports as a case study. For this purpose, mathematical models that accounted for both seasonality and trends in the time series were employed and then compared. The study confirmed that the epidemic crisis led to a marked decline in passenger traffic at Polish seaports. The forecasts produced were generally higher than the actual figures, highlighting the disruptions caused by the pandemic. This finding is reinforced by the comparison of the results obtained by three different mathematical models. Based on the values of the information criteria and the comparison of actual data with the forecasts, the SARIMA model proved to be the most accurate. The Holt-Winters model also demonstrated high fitting and predictive performance. The STL model offered intriguing insights as well, with its time series decomposition enabling a detailed analysis of individual components in light of the disruptions caused by the pandemic. In summary, the comparative analysis of the proposed models (i.e., SARIMA, Holt-Winters, and STL) has shown their usefulness in forecasting changes in the number of passengers in Polish seaports in the face of disruptions such as the COVID-19 pandemic. These models can be an effective decision-making support tool, helping to limit the negative effects of future epidemic threats. Conclusions based on these models can be used to develop strategies in the event of a recurrence of similar challenges.

However, despite the obtained results, the study has several limitations. First of all, the analysis was based on data concerning Polish seaports only, which may limit the universality of the proposed models and the possibility of generalizing conclusions for other countries. Another limitation is the lack of an in-depth qualitative analysis, which could complement the analyzed quantitative results by better understanding the factors determining the variability in passenger traffic. It is also worth noting that the study focused on the relatively short-term effects of the pandemic, which may ignore long-term changes in passenger behavior and preferences. An additional limitation of the study was the availability of only quarterly data, which may translate into the predictive performance of the proposed models and, therefore, may not reflect changes occurring in the months following the outbreak of the pandemic. Hence, it may not take into account the full scope of external influences, such as global economic changes or current initiatives related to crisis management.

Taking into account the obtained results, further research should focus primarily on extending the analyses to other countries or regions in order to understand global trends and their local diversity. This would also allow for an assessment of the universality of the developed forecasting models in terms of their application to other transport markets. Another direction of research may be to consider more advanced models using, among others, machine learning algorithms and analyses based on Big Data sets. This would make it possible to consider additional factors, which in turn would improve the performance of the models and the precision of the forecasts. Such studies should include a detailed analysis of the impact of external factors, including state policy and sanitary regulations. Another important direction of the research is to prepare recommendations and proposals for solutions aimed at increasing the safety of the Polish maritime transport sector in the event of similar events in the future. The authors plan to conduct more detailed analyses in this area in future studies.

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