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Forecasting Ro-Ro Freight Transportation Demand at Samsun Port: A Hybrid Method Approach

Samsun Limanı'nda Ro-Ro Yük Taşımacılığı Talebinin Tahmini: Hibrit Bir Yöntem Yaklaşımı

Türk Denizcilik ve Deniz Bilimleri Dergisi Cilt: 10 Sayı: 2 (2024) 71-88

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ABSTRACT

Türkiye's extensive coastline and geopolitics position necessitates the importance of Ro-Ro transportation with neighbouring countries. Türkiye's rapidly growing Ro-Ro transportation significantly contributes to imports and exports, which is of great importance to the national economy. Samsun Port is one of the most active ports in Türkiye's Ro-Ro transportation sector, operating in the Black Sea region. This study examined Ro-Ro transportation at Samsun Port, and future cargo forecasting was conducted. For this purpose, artificial neural networks and time series analysis methods were combined. Input variables used in the study included the number of Ro-Ro ships arriving at the port between 2009 and 2021, population figures, a specialized CPI indicator (fresh fruits and vegetables), and export values. The output variable was the amount of cargo carried by Ro-Ro ships. According to the results obtained, it was observed that Samsun Port would have sufficient capacity for Ro-Ro transportation in the next 27 months in terms of wharf, port area, and operational space.

Keywords: Samsun Port, Ro-Ro transportation, Port capacity, Forecasting

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ÖZET

Türkiye'nin geniş kıyı şeridi ve jeopolitik konumu, komşu ülkelerle Ro-Ro taşımacılığının önemini gerektirmektedir. Türkiye'nin hızla büyüyen Ro-Ro taşımacılığı, ülke ekonomisi için büyük önem taşıyan ithalat ve ihracata önemli katkı sağlamaktadır. Samsun Limanı, Karadeniz bölgesinde faaliyet gösteren, Türkiye Ro-Ro taşımacılığı sektörünün en aktif limanlarından biridir. Bu çalışmada Samsun Limanı'ndaki Ro-Ro taşımacılığı incelenmiş ve geleceğe yönelik kargo miktarı tahminlemesi yapılmıştır. Bu amaçla yapay sinir ağları ve zaman serisi analiz yöntemleri birleştirilmiştir. Çalışmada kullanılan girdi değişkenleri arasında 2009-2021 yılları arasında Samsun Limanı'na gelen Ro-Ro gemilerinin sayısı, nüfus rakamları, özel tanımlı TÜFE göstergesi (taze meyve ve sebze) ve ihracat değerleri yer almaktadır. Çıktı değişkeni ise Ro-Ro gemilerinin taşıdığı kargo miktarıdır. Elde edilen sonuçlara göre Samsun Limanı'nın önümüzdeki 27 ay içerisinde iskele, liman alanı ve operasyonel alan açısından Ro-Ro taşımacılığı için yeterli kapasiteye sahip olacağı görülmüştür.

Anahtar sözcükler: Samsun Limanı, Ro-Ro taşımacılığı, Liman kapasitesi, Tahminleme

1. INTRODUCTION

Ro-Ro transportation has become a significant component of contemporary maritime transportation (Zis and Psaraftis, 2017). Minimizing the vessel's waiting time in ports to reduce transportation freight costs and maximizing profit by increasing the number of voyages are fundamental objectives of this transportation method (Morales-Fusco *et al*., 2010; Jiang *et al*., 2017). Consequently, as the competitive environment within maritime transportation continues to intensify, the importance of Ro-Ro transportation is correspondingly increasing. This transportation model began prominently emerging in global maritime trade during the 1940s, originating in the Scandinavian countries. Initially focused on passenger transportation in European ports, it gradually adapted to cargo transportation, evolving into deep-sea transportation (Özdemir and Deniz, 2013).

Ro-Ro transportation in Türkiye gained significance in 1985 with the commencement of ferry services between Trabzon (Türkiye) and Sochi (Russia) by the M/F Avrasya ferry at Trabzon Port. This development rapidly stimulated the growth of Ro-Ro transportation in Türkiye due to extended queues at border crossings, prolonged waiting times, high highway tolls, inadequate road infrastructure, and safety concerns associated with land-based transportation (Yıldırım, 2006). The increasing volume of trade and the challenges associated with road transportation necessitated the opening new Ro-Ro routes as an alternative to costly air transportation. Routes such as Samsun-Novorosisky, Samsun-Tuapse, Rize-Poti, and Zonguldak-Odessa were established; however, these routes have exhibited variability over time or have been discontinued depending on international developments (Başar *et al*., 2015).

The transportation infrastructure of Samsun province holds significant potential, with its road connections extending to the Samsun-Sivas railway and the Mersin port (Kahveci, 2021). Furthermore, Çarşamba Airport is crucial in providing access to domestic and international routes for reaching Samsun port. The hinterland of Samsun Port's Ro-Ro transportation is illustrated in Figure 1.

Multimodal transportation enables the transition between different modes of transport. Ro-Ro transportation, particularly due to the easy integration of land vehicles onto ships, offers a more flexible and reliable transport option. In Ro-Ro transportation originating from Samsun Port, Trabzon Port, and Zonguldak Ports, the transfer of wheeled vehicles occurs between these ports. Generally, Ro-Ro transportation from Black Sea ports to ports in Russia and Ukraine is increasingly emphasizing the importance of multimodal transportation (Görçün and Görçün, 2018).

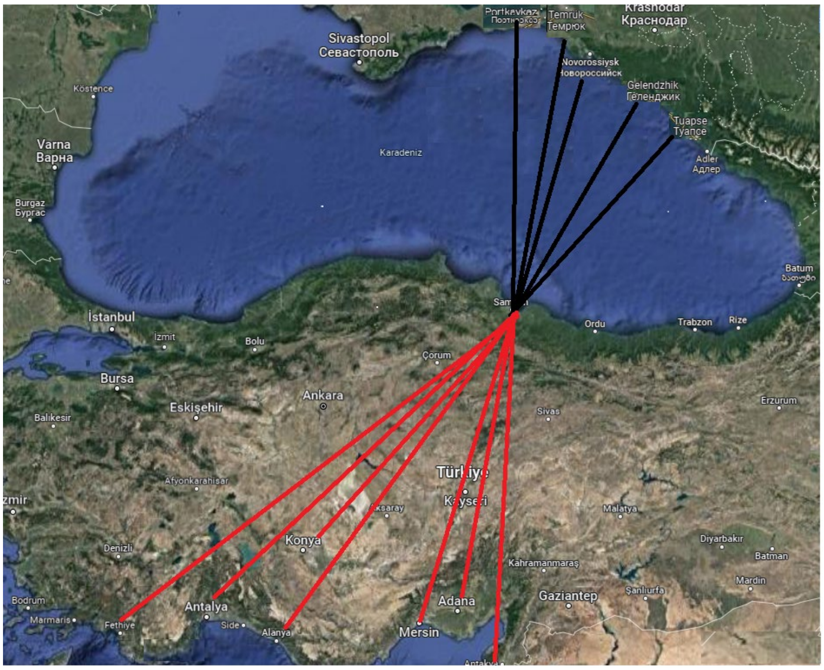

Figure 1. Samsun Port Ro-Ro Transportation Hinterland

Table 1 presents the vehicle statistics for departures, arrivals, and the total number of vehicles at Samsun Port between 2015 and 2022. A decrease in transported vehicles can be observed between 2015 and 2016. This decline can be attributed to the diplomatic crisis that ensued when a Russian jet entered Turkish airspace in 2015 and was subsequently shot down by Türkiye, leading to Russia imposing embargoes on Türkiye in various sectors. However, the issues were resolved through bilateral government negotiations, and maritime transportation services resumed (Köstem, 2018). An increase in demand for fresh fruits and vegetables in Russia and the incentives periodically provided to companies involved in exporting seasonal products from Türkiye have contributed to expanding the shipping fleets of firms operating at Samsun Port.

The traffic of Ro-Ro transportation was concentrated in Novorossiysk, Tuapse, and Gelendzhik ports between 2015 and 2018. However, after 2018, Gelendzhik Port altogether ceased its Ro-Ro ship services. Consequently, the number of Ro-Ro ships at Samsun Port increased, and there was a search for alternative ports like Kavkaz and Temruk. This strategy minimized the queue for Ro-Ro ships to dock at Russian Ro-Ro ports. As depicted in Figure 2, the increase in Ro-Ro transportation at Samsun Port is evident each passing year. Parallel to this increase, the capacity of Samsun Port should be closely monitored, and potential adjustments should be planned, considering that infrastructure developments will take time.

In this study, Ro-Ro capacity forecasting for Samsun Port is conducted using artificial neural networks and time series analysis methods. The continuation of the article is structured as follows. In the second section, existing studies in the literature related to port capacity forecasting are reviewed. The third section presents the materials and methods used in the article. The fourth section includes the results obtained from the analysis of the existing data. In the fifth section, the obtained results are discussed, and finally, the sixth section presents conclusions, recommendations, limitations, and suggestions for future research.

Table 1. Vehicle Statistics Transported on Ro-Ro Lines with International Connections in Samsun Port (Atlantis, 2022)

Year	Port	Arriving Vehicle	Outgoing Vehicle	Total Transported Vehicles
2022	Novorossiysk	1850	2618	4468
	Tuapse	16048	18167	34215
	Kavkaz	16782	17187	33969
	Temruk	2718	3178	5896
Total				**78548**
2021	Novorossiysk	10081	15815	25896
	Tuapse	18949	30013	48962
	Kavkaz	592	526	1118
	Temruk	1790	1961	3751
Total				**79727**
2020	Novorossiysk	5381	6062	11443
	Tuapse	17737	20703	38440
	Temruk	1257	1300	2557
Total				**52440**
2019	Novorossiysk	252	7876	8128
	Tuapse	626	31839	32465
Total				**43150**
2018	Novorossiysk	452	1666	2118
	Tuapse	1733	4269	6002
	Gelendzhik	4712	6748	11460
Total				**19580**
2017	Novorossiysk	3305	3498	6803
	Tuapse	1642	1670	3312
	Gelendzhik	5484	5432	10916
Total				**21031**
2016	Novorossiysk	1568	1845	3413
	Gelendzhik	3040	2863	5903
Total				**20232**
2015	Novorossiysk	2791	7440	10231
	Tuapse	1138	3244	4382
	Gelendzhik	7071	6782	13853
Total				**28466**

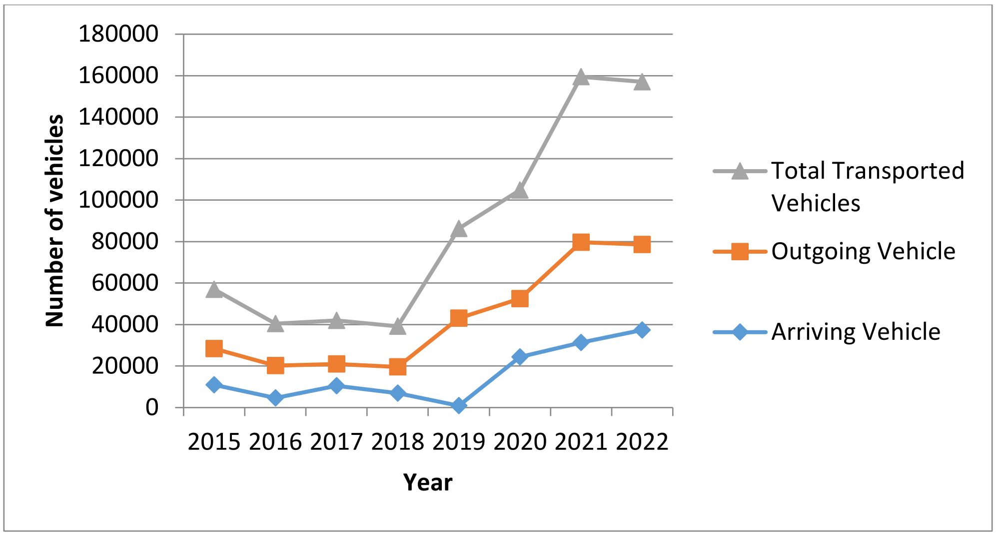

Figure 2. Vehicle Statistics Chart on Ro-Ro Lines with International Connections in Samsun Port (Atlantis, 2022)

2. LITERATURE REVIEW

When examining the literature on transportation demand for ports, studies are frequently focused on forecasting container demand. Simultaneously, these forecasts are often conducted using a hybrid approach, combining multiple models. The parameters used in the forecasting stage are commonly selected from the macroeconomic indicators of the examined region and its hinterland.

Eskafi *et al.* (2021) conducted port capacity forecasting for Isafjordur Port in Iceland, where the handling of different types of cargo takes place. They employed a mutual information approach and Bayesian statistics to eliminate uncertainties in the model and parameters, respectively. A total of six macroeconomic variables were used for forecasting: national gross domestic product (GDP), average annual consumer price index (CPI), world GDP, national export trade volume, national import trade volume, and national population data. The analysis revealed that containerized cargo at Isafjordur Port is projected to increase in future projections, while bulk cargo transported outside of containers is expected to decrease.

Pang and Gebka (2017) utilized three different models to forecast monthly port and individual terminal container transportation demand between 2003 and 2013. These models included Seasonal Autoregressive Integrated Moving Average (SARIMA), Seasonal Holt-Winters with Additive Seasonality (MSHW), and Vector Error Correction Model (VECM). The performance of prediction models was evaluated based on mean absolute error and the square root of mean square error. Results indicated that the MSHW model provided the most accurate predictions for total container volume, while SARIMA produced the least satisfactory in-sample model fit. VECM yielded the best model fits and predictions for individual terminals. Results suggested that the obtained capacity forecasts would be adequate when considering the confidence interval of measurements.

Rashed *et al.* (2018) developed a three-step approach combining the autoregressive distributed lag model (ARDL) with economic scenarios. The empirical analysis relied on a time series spanning from 1995 to 2017 for container volume in the Hamburg-Le Havre (H-LH) range and economic indices. Data such as exports, imports, GDP, and loaded and unloaded container quantities were used as a control group for the period from 2015 to 2017. The study demonstrated an average elasticity of 1.4, indicating a long-term relationship between trade indices and container volume in the H-LH range.

Dragan *et al.* (2021) conducted a study on demand forecasts for supply-demand cargo transportation at the Adriatic Port of Koper and introduced a new forecasting approach called the DFA-ARIMAX model. This model integrates information obtained through dynamic factor analysis (DFA) into the ARIMAX prediction model and includes principal component regression and a Monte Carlo framework to identify port-specific indicators. Using purchasing power, GDP, export, and import data, they compared the accuracy of forecasts obtained with actual data and emphasized the satisfactory performance of the forecasting.

Moscoso-López *et al.* (2019) presented a hybrid approach using Artificial Neural Networks (ANN) and Support Vector Regression (SVR) models by utilizing eight years of daily time series data from Algeciras Port. The model predicted the next seven days and was compared with realized data, revealing that the hybrid use of both models provided superior results compared to individual usage. The authors highlighted the potential usefulness of the algorithm in improving port planning and management.

The increasing demand for maritime transportation, driven by population growth and economic expansion, has gradually started to strain port infrastructure capacities over the years. A review of the literature reveals that forecasting models are frequently employed to balance supply and demand between maritime transportation and port capacity. However, there has been no growth and capacity forecasting study conducted for Ro-Ro transportation at Samsun Port. Within this context, this study holds significant importance in filling this gap in the literature.

3. MATERIAL AND METHOD

This study provides a 27-month forecast of the cargo volume transported by Ro-Ro vessels at Samsun Port. To perform this forecasting, input data encompassing population figures, the Consumer Price Index (CPI), export figures, and the number of Ro-Ro vessels from January 2009 to September 2021 were utilized. Time series analysis and artificial neural networks were applied to these data for forecasting. The primary reason for selecting data between 2009 and 2021 in this study is the absence of data from other years at the port authority from which the data was obtained.

The selection of input variables benefited from previous studies in the literature. These studies indicate that the macroeconomic indicators of the port and its surroundings are the factors that most influence transportation demand (Gökkuş et al., 2017; Gosasang et al., 2018; Eskafi et al., 2021). The aim was to have the selected factors interact with each other at the minimum level. Otherwise, by influencing each other, these factors may lead to overestimating prediction quantities.

This study aims to forecast the amount of cargo carried by Ro-Ro ships departing from Samsun Port. It will be determined whether Ro-Ro transportation from Samsun Port, including the number of ships departing from the port and the cargo transport from the port, affects the port's capacity. In this context, the preliminary hypothesis of the study is defined as "The amount of cargo transported from Samsun Port in Ro-Ro transportation will increase by the end of 2023.

3.1. Data Set

In determining input variables, a literature review was conducted, followed by the compilation of parameters commonly used in analogous forecasting studies. Subsequently, the created parameter list was scrutinized by experts, and the four most significant parameters influencing the cargo volume in Ro-Ro transportation were included as input variables in the study.

In this context, the number of vessels, which plays a crucial role in determining the cargo volume, was utilized as an input variable (Czermański, 2017). Furthermore, the Consumer Price Index (CPI), which exerts a mutual influence on the transported goods and freight prices, was considered an input variable because it affects the quantity of cargo transported by Ro-Ro (De Monie *et al.*, 2011). Additionally, the population of Samsun is recognized as a significant factor influencing port activities. It is well-known that port activities increase in regions with a dense population (Yüksekyıldız, 2010; Czermański, 2017). Lastly, the monetary values of goods exported from Samsun Port also play a pivotal role in forecasting the cargo volume to be transported. Variations in export figures from the port will directly impact the increase and decrease in cargo volume, making it an important input variable in the study (Guo and Yang, 2019).

The information related to the data used in the study was obtained from datasets provided by official institutions through online sources and compiled in a format suitable for the study. The input variable, which consists of the number of Ro-Ro vessels, and the output variable, which involves the cargo volumes transported by Ro-Ro, were obtained from the Samsun Port Authority (Samsun Port Authority, 2021). The input variables, including the Consumer Price Index (CPI) and population values, were sourced from the Turkish Statistical Institute, while the export figures for Samsun province were retrieved from the website of the Türkiye Exporters Assembly (TIM, 2021; TURKSTAT, 2021a; TURKSTAT, 2021b).

3.2. Time Series Analysis

Time series are numerical quantities that represent the successive changes of variables from one period to another, depending on the values those variables have taken. While the obtained data don't need to occur sequentially, having them arranged at regular intervals can be beneficial to understanding how the series is formed (Box *et al.*, 2015; Montgomery *et al.*, 2015).

In time series analysis, numerous methods have been developed for predicting future observations using past and current period observation values. These methods are illustrated in Figure 3 (Oğhan, 2010)

In the conducted study, the Exponential Smoothing method of Winters (1960), which is one of the exponential smoothing methods, was employed. This method is used for forecasting time series that exhibit seasonal fluctuations and trends. The time series components that this method applies to are the seasonal component, the average level, and the slope. The process of updating forecasts in time series that adhere to the mathematical inequalities is calculated sequentially according to the following formulation (Oğhan, 2010).

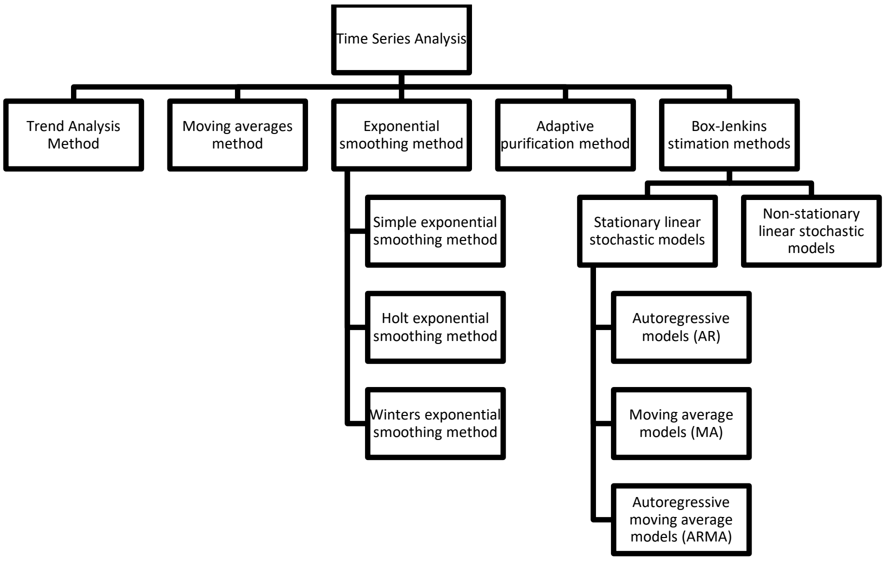

Figure 3. Types of Time Series Analysis Methods (Oğhan, 2010)

Update the average level:

$$a_T = \alpha\left(Y_t - M_t\left(T-s\right)\right) + \left(1-\alpha\right)\left(a_{T-1} + b_{T-1}\right) \quad (1)$$

It is represented as follows:
$a_T =$ New smoothing forecast for the average level at period T
α = Smoothing coefficient for the average level
$Y_t - M_t\left(T-s\right) =$ The deseasonalized original data at period T
$a_{T-1} =$ The old smoothing forecast for the average level at period (T-1)
$b_{T-1} =$ The old smoothing forecast for the slope at period (T-1)

Update the slope:

$$M_{T+S}\left(T\right) = \delta\left(Y_T - a_T\right) + \left(1-\delta\right)M_T\left(T-s\right) \quad (2)$$

It is represented as follows,
$M_{T+S}\left(T\right) =$ New smoothing forecast for the seasonal component in period T
$\delta =$ Smoothing coefficient of seasonal component
$Y_T - a_T =$ Seasonal variation in data obtained by subtracting a new estimate of the mean level from the original data
$M_T\left(T-s\right) =$ It is the old smoothing coefficient of the seasonal component in the period (T-s).

Estimated values of the observation in the additive model:

$$\hat{Y}_{T+1} = a_T + b_T + M_{T+1}\left(T+1-s\right) \quad (3)$$

It is represented as follows,
$\hat{Y}_{T+1} =$ Forecast for the (T+1)th period
$a_T =$ Smoothing estimate of the average level in period T
$b_T =$ Smoothing estimate for slope in period T
$M_{T+1}\left(T+1-s\right) =$ It is a smoothing estimate for the period (T+1) made in the period (T+1-s).

Updating predictions in series suitable for the multiplicative model:

$$a_T = \alpha\left[\frac{Y_T}{M_T\left(T-s\right)}\right] + \left(1-\alpha\right)\left(a_{T-1}+b_{T-1}\right) \qquad (4)$$

$$b_T = \gamma\left(a_T - a_{T-1}\right) + \left(1-\gamma\right)b_{T-1} \qquad (5)$$

$$M_{T+S}\left(T\right) = \delta\left[\frac{Y_T}{a_T}\right] + \left(1-\delta\right)M_T\left(T-s\right) \qquad (6)$$

It is done in the form.

Predictive values of observation in multiplicative model:

$$\hat{Y}_{T+1} = \left(a_T + b_T\right) * M_{T+1}\left(T+1-s\right) \qquad (7)$$

It is done in the form (Kadılar, 2005).

The values for a and b in the equations were obtained using the decomposition method and regression analysis method in Winters' exponential smoothing method. When employing Winters' exponential smoothing method, to generate reliable results for forecasts, like in the simple exponential smoothing method, the smoothing coefficient MAD (Mean Absolute Deviation) representing the mean of the least squares for prediction confidence intervals is calculated (Kadılar, 2005)

Exponential smoothing methods, which take into account all factors used in the calculation of time series, are considered suitable techniques in contemporary applications due to their cost-effectiveness and the minimal time required for their implementation (Oğhan, 2010).

3.3. Artificial neural networks

Artificial neural networks (ANNs) have emerged through the mathematical modelling of the learning process, inspired by the stages of human brain learning (Kabalcı, 2014). Within this network, artificial neurons functionally resemble the working system of biological neurons (Şenalp, 2017). Structurally, ANNs consist of numerous interconnected nerve cells, referred to as neurons. These neurons, termed as such, constitute the fundamental processing mechanism within ANN (Figure 4).

3.3.1. Artificial Neural Networks Structure

Artificial neural networks are formed by the functional structures of multiple artificial nerve cells coming together as nodes, neurons, or nerves. Generally, the cells are organized into three layers, and the parallel assembly of elements creates each layer. These layers are as follows (Öntemel, 2016):

- Input layer: The cells in this layer are responsible for receiving information from the external world and transmitting it to intermediate layers. In some networks, there is no information processing in the input layer.
- Hidden layers: These layers process the information received from the input layer and send it to the output layer. Multiple intermediate layers can exist in a network.
- Output layer: The cells in this layer process the information received from the intermediate layers and generate the output that the network should produce for the input set presented in the network's input layer. The produced output is then transmitted to the external world (Figure 5).

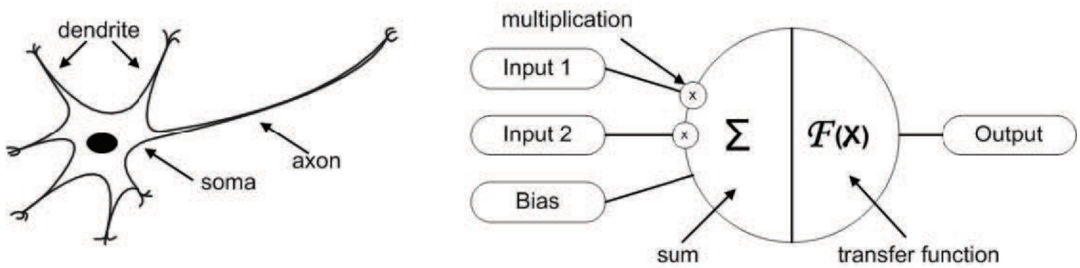

Figure 4. Biological Neural Cell and Artificial Neural Network (Krenker *et al*., 2011)

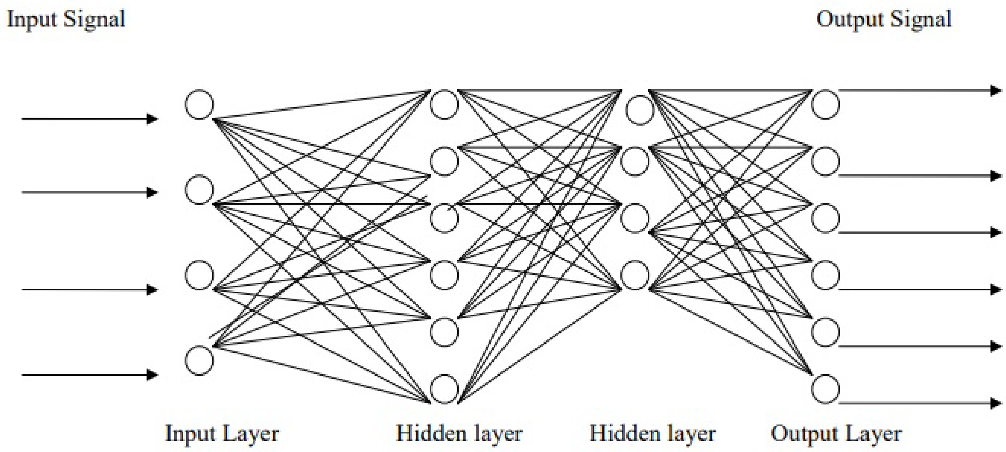

Figure 5. Multilayer feedforward ANN structure (Eluyode and Akomolafe, 2013)

4. RESULTS

4.1. Time Series Analysis Input Variables Forecasting

In the initial phase of the study, Time Series Analysis was conducted using the exponential smoothing method with the assistance of the STATISTICA software package. The primary reason for choosing this method was that in models created using other time series analyses, the significance coefficients often turned out to be relatively low, failing to provide accurate results (Winters, 1960; Oğhan, 2010). During time series analysis, the method to be used for making the best predictions based on the entered values can be determined by the program. Therefore, in the study, the prediction method that provides the best forecasting and has the lowest error rate has been preferred. In this context, since the lowest error rate was observed to be obtained using the linear regression method, this method has been chosen in the study.

In the analyses conducted to form input variables, the additive method was used for ship numbers, population, and CPI forecasts, while the multiplication method was employed for export figures. The parameters Alpha, Delta, and Gamma coefficients, and error terms for each input value, obtained through time series analysis, are provided in Table 2. Furthermore, the resulting forecast results are presented in Table 3 and illustrated in Figure 6.

The time series analysis conducted in this study has shown the presence of seasonal fluctuations in the number of ships departing from Samsun Port over 27 months. It is predicted that 1664 ships will depart from the port by the end of December 2023. Examination of historical data reveals periodic increases and decreases in the number of Ro-Ro ships, with variations occurring in the number of ships departing from the port during specific periods. Therefore, the forecasting results exhibit a similarity in structure to previous periods (MAPE=68.867). The origin of achieving a high MAPE (Mean Absolute Percentage Error) value in the prediction of the incoming ship count is attributed to the significant fluctuations during the previously mentioned jet crisis period.

The time series analysis conducted for the Consumer Price Index (CPI) values in Samsun province indicates that the increasing trend observed in previous periods is expected to continue in future periods. It is forecasted that the CPI value will reach 1128.422 by December 2023. Given the current economic crisis and exchange rate fluctuations, relevant institutions (Turkish Statistical Institute, Central Bank, Ministry of Trade, etc.) have also indicated that CPI values will likely increase in the coming periods. Therefore, it is assumed that the CPI forecasts made in this study provide accurate results, considering the current economic conditions (MAPE=6.097).

Table 2. Prediction Parameters Obtained for Input Variables

Value	Ship number	CPI	Export figures	Population
Method	Additive	Additive	Multiplication	Additive
Alpha coefficient	0.284	1.000	0.330	1.000
Delta coefficient	0.000	0.502	0.000	1.000
Gamma coefficient	0.043	0.000	0.052	0.000
Mean error	-3.468	-0.673	989.422	-65.310
Mean absolute error	11.405	18.860	7354.116	649.509
Sums of squares	33863.126	102618.654	19135315146	389408409.285
Mean square	221.327	670.710	125067419.255	2545153.002
Mean percentage error	-34.055	-0.553	-2.346	-0.005
Mean abs. perc. error	68.867	6.097	16.440	0.050

Table 3. Input Variables Time Series Analysis Prediction Results

No	Date	Number of ships prediction (pcs)	CPI prediction (index value)	Export value prediction (thousand US $)	Population prediction (people)
154	1.10.2021	59	768.744	137137	1346863
155	1.11.2021	66	777.787	135444	1347815
156	1.12.2021	67	797.722	135938	1348789
157	1.01.2022	50	850.289	124669	1348117
158	1.02.2022	48	872.204	129904	1349030
159	1.03.2022	52	888.924	149224	1349949
160	1.04.2022	50	893.423	140063	1350872
161	1.05.2022	62	873.126	150447	1351779
162	1.06.2022	61	863.118	137569	1352726
163	1.07.2022	47	860.805	151691	1353699
164	1.08.2022	50	861.555	146143	1354642
165	1.09.2022	48	879.213	174269	1355590
166	1.10.2022	67	915.655	173446	1356543
167	1.11.2022	74	926.817	170530	1357501
168	1.12.2022	75	948.901	170408	1358481
169	1.01.2023	58	1003.648	155628	1357815
170	1.02.2023	56	1027.776	161508	1358734
171	1.03.2023	60	1046.739	184808	1359658
172	1.04.2023	59	1053.514	172811	1360587
173	1.05.2023	70	1035.526	184951	1361500
174	1.06.2023	70	1027.859	168528	1362452
175	1.07.2023	56	1027.923	185200	1363431
176	1.08.2023	59	1031.083	177842	1364380
177	1.09.2023	57	1051.185	211397	1365334
178	1.10.2023	76	1090.108	209755	1366293
179	1.11.2023	83	1103.786	205616	1367257
180	1.12.2023	84	1128.422	204878	1368243

The time series analysis conducted based on the export figures from Samsun province considers the seasonality of export figures. Looking at export values with periodic increases and fluctuations, it is observed that trend values are on an increasing trajectory. As a result of the forecasting, it is anticipated that export figures will continue to rise in the upcoming 27-month period, reaching around 204878 thousand US dollars by the end of 2023. Considering the current conditions, with the significant increase in the exchange rate of the US dollar, which has led to record-breaking exports in the economic landscape, the export forecast in this study appears to be quite successful (MAPE=16.440). The high MAPE value observed here, similar to the incoming ship count, is attributed to the effects of significant fluctuations during the jet crisis period.

In the population figures for Samsun province, which served as the final input variable for the prediction, it is estimated that the population will be 1368243 people by the end of December 2023. Due to Samsun's geographically and economically advantageous position, it is known to receive constant migration from neighbouring provinces. When examining data from previous periods, it is evident that the population of Samsun province has consistently increased over the years. Therefore, these forecasts reflect an unchanging pattern, with the population increasing. Looking at TURKSTAT (Turkish Statistical Institute) data for population forecasts by years and provinces, the predictions made for Samsun province are found to be quite similar to TURKSTAT data (MAPE=0.050).

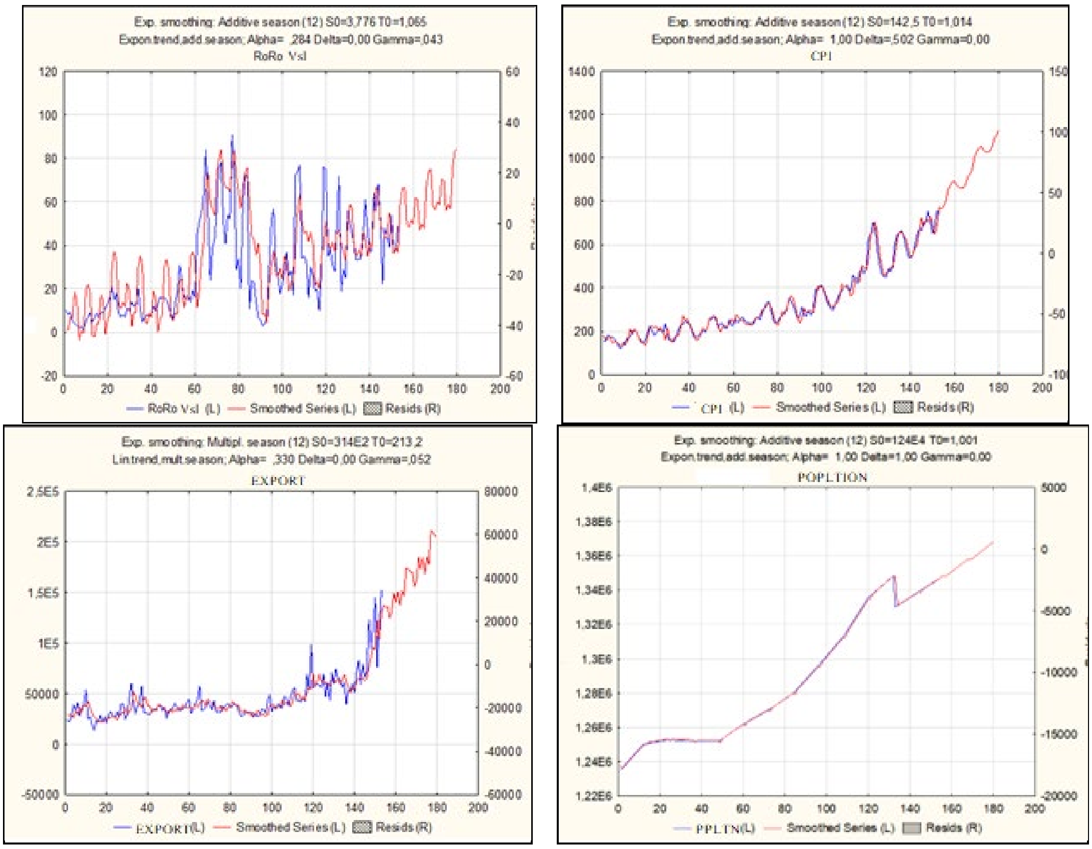

Figure 6. Input Variables Prediction Graphs

4.2. Output Variable Prediction with Artificial Neural Networks

Using the results of Time Series Analysis for input variables, the prediction of the output variable, which is the amount of cargo transported by Ro-Ro ships, was carried out using the "Artificial Neural Networks" module in MATLAB. For this purpose, an artificial neural network architecture consisting of four input variables and one output variable was created. The constructed artificial neural network includes one hidden layer with ten neurons and one output layer with one neuron (Figure 7).

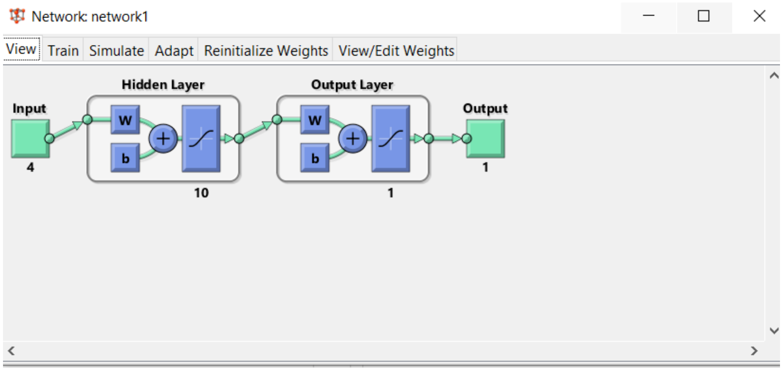

Figure 7. Artificial Neural Network Architecture

In determining the number of layers and neurons in the constructed artificial neural network, a trial-and-error method was used to identify the artificial network that yielded the best results. The maximum error threshold (max_fail) for training the artificial network was set to 1000 as a parameter. No changes were made to the other values.

Before creating the artificial neural network, various learning methods and transfer functions were employed through a trial-and-error approach to obtain output results. It was observed that the best results were achieved when using the backpropagation weight/bias learning function "learngdm" with momentum and the variable learning rate gradient descent "traingdx" algorithm. The "tansig" transfer function was utilized. After training the constructed artificial neural network, the performance values and regression coefficients are presented in Figure 8.

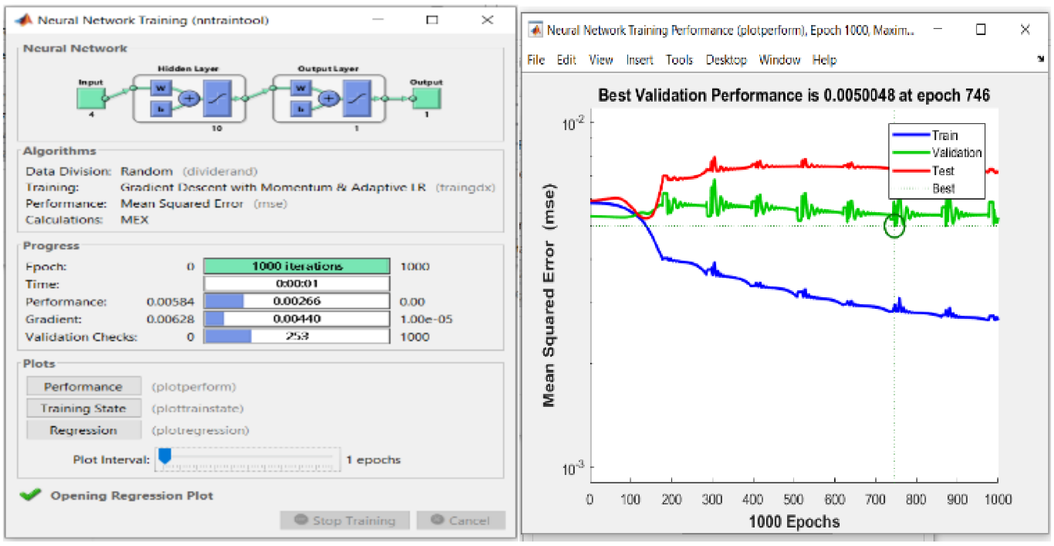

Figure 8. ANN Training and Performance Screen

The results obtained from the artificial neural network regression in the study reveal high values, indicating a significantly high predictive capability of the constructed network. Figure 9 shows a training accuracy rate of 95.6% was achieved, with a validation rate of 92.5% for the training data and a validation rate of 93.5% for the test data. The overall accuracy rate of the entire network architecture was 94.5%. Examining these accuracy rates, it is evident that the predictions will yield highly accurate results

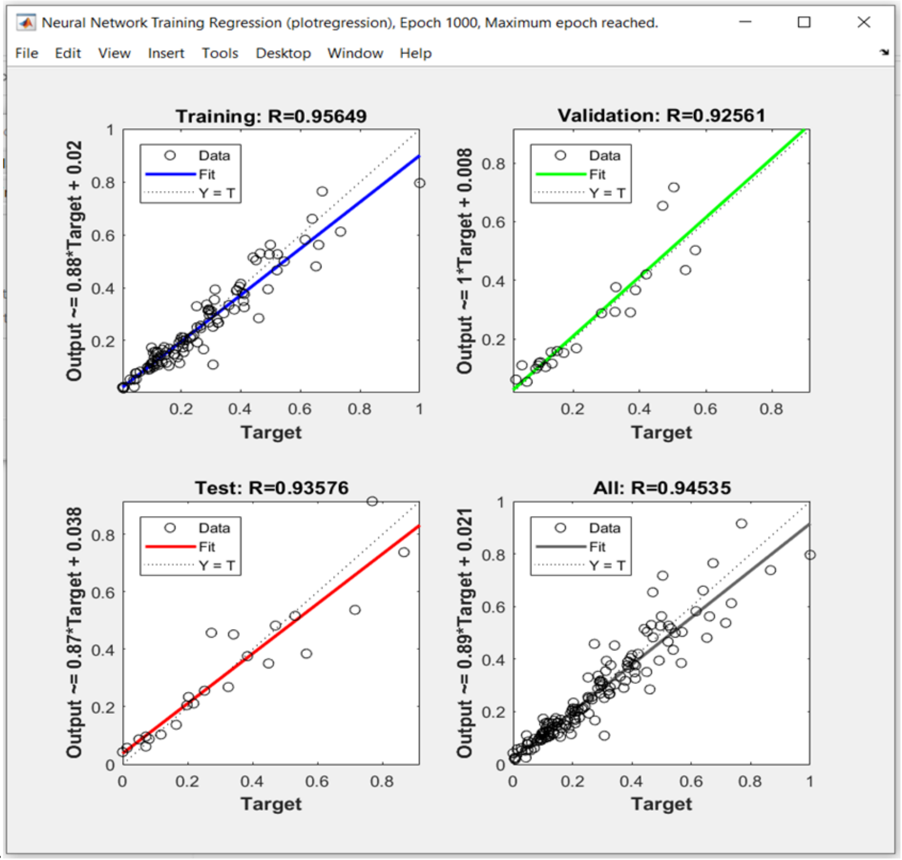

Figure 9. ANN Regression Values Screen

Following the training and testing processes, the artificial neural network was provided with 27-month data for the four input variables (Population, CPI, Export, Ro-Ro Count), and the network was tasked with making predictions. The artificial neural network's predictions for the 27-month Ro-Ro cargo amount (in tons) to be transported according to the new data are presented in Table 4. According to the predictions, the amount of Ro-Ro cargo to be transported from Samsun in December 2023 is estimated to be 65774.9 tons. The total cargo amount to be transported over the 27 months is projected to be 1622448.8 tons. The results obtained from forecasting with artificial neural networks reveal that the data exhibit seasonality similar to past years and a slight trend, as depicted in Figure 10. The reliability of the hybrid algorithm was tested by comparing the obtained total predicted cargo handling values with the actual data. The predictions were subjected to correlation analysis with the actual transportation quantities obtained from Samsun Port Authority, resulting in an accuracy rate of 73% (Table 5.) (Samsun Port Authority, 2023).

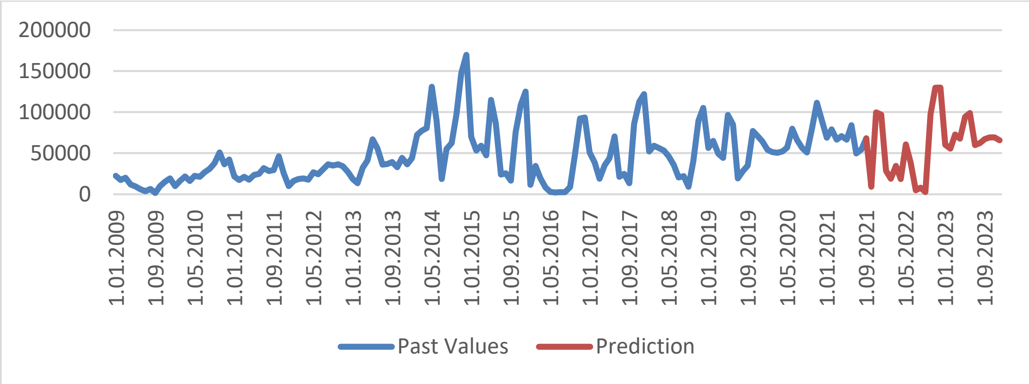

Figure 10. Ro-Ro Handling Past Values and ANN Prediction Results

Table 4. Estimation of the Amount of Cargo to be Transported by Ro-Ro in Samsun Port

Date	Prediction (tons)	Date	Prediction (tons)
1.10.2021	9338.639	1.11.2022	129844.874
1.11.2021	99892.975	1.12.2022	129986.780
1.12.2021	97094.882	1.01.2023	60328.826
1.01.2022	28780.391	1.02.2023	55799.336
1.02.2022	18903.814	1.03.2023	72683.198
1.03.2022	34420.243	1.04.2023	67653.165
1.04.2022	18735.536	1.05.2023	94285.518
1.05.2022	60572.615	1.06.2023	99068.103
1.06.2022	38428.898	1.07.2023	60092.792
1.07.2022	4728.207	1.08.2023	62156.942
1.08.2022	7855.984	1.09.2023	67414.831
1.09.2022	2706.098	1.10.2023	69250.786
1.10.2022	97290.902	1.11.2023	69359.523
		1.12.2023	65774.926
		Total	**1622448.781**

Table 5. Correlation Analysis Between Amount of Cargo Transported and Hybrid Model Estimation

Date	Actual (tons)	Prediction (tons)	Date	Actual (tons)	Prediction (tons)
1.10.2021	75210	9338.639	1.11.2022	148425	129844.874
1.11.2021	65010	99892.975	1.12.2022	139900	129986.780
1.12.2021	47930	97094.882	1.01.2023	76400	60328.826
1.01.2022	45925	28780.391	1.02.2023	53240	55799.336
1.02.2022	86025	18903.814	1.03.2023	72400	72683.198
1.03.2022	100175	34420.243	1.04.2023	89660	67653.165
1.04.2022	63500	18735.536	1.05.2023	76525	94285.518
1.05.2022	68225	60572.615	1.06.2023	90100	99068.103
1.06.2022	58775	38428.898	1.07.2023	40325	60092.792
1.07.2022	111175	4728.207	1.08.2023	93750	62156.942
1.08.2022	75210	7855.984	1.09.2023	65000	67414.831
1.09.2022	65010	2706.098	1.10.2023	100450	69250.786
1.10.2022	47930	97290.902	1.11.2023	110275	69359.523
			Calculated correlation		**0.728**

5. DISCUSSION

Based on predictions derived from time series analysis of input variables, an artificial neural network method was employed to forecast the total cargo volume transported by Ro-Ro (Roll-on / Roll-off) within 27 months. The results of this forecasting, conducted using MATLAB, indicate an estimated total cargo transportation of 1622448.8 tons from Samsun port until the end of 2023. The findings reveal that the predicted cargo volumes exhibit seasonal increases and decreases when examined monthly. When these prediction results are compared with previous period data, they demonstrate a striking resemblance in values, and nearly identical patterns of both increases and decreases are observed during similar periods.

According to data from the Port Operators Association of Turkey (TURKLIM), Samsun port's annual handling capacity is reportedly 50000 vehicles. Assuming that each truck has a capacity of approximately 28-30 tons, the Ro-Ro cargo capacity of the port ranges between 1400000 tons and 1500000 tons annually. The estimated Ro-Ro cargo volume for the 27 months amounts to 1622448.8 tons. For 2023 alone, an estimated 843867.9 tons of cargo transport are projected. Based on this assessment, it can be concluded that Samsun port's capacity is deemed sufficient (TURKLIM, 2021).

When examining the research conducted for Samsun port, particularly regarding the prediction of Ro-Ro transportation in the upcoming periods, there is limited existing literature on this topic. Nevertheless, studies related to other types of cargo can be found. In a study conducted by Yüksekyıldız (2010), the estimation of cargo volume to be handled in Samsun port was carried out. The study employed regression analysis and conducted cargo predictions based on different scenarios. The study results indicate an increase in the cargo handling volumes from Samsun port over the years. This study's findings align with the results of the study conducted by Yüksekyıldız (2010), which also estimated an increase in the handled cargo volume in both works.

In the study conducted by Özdemir (1993), the evolutionary history of Ro-Ro transportation in Türkiye and the technical specifications of Ro-Ro vessels during this development process were analyzed in detail. The research underscores that Ro-Ro transportation has undergone a rapidly evolving historical development. This study comprehensively examines the shift from land to sea transportation over time by truck fleets, which play a significant role in trade between European countries and Türkiye. The findings obtained by Özdemir are corroborated by our article for Samsun Port as well. Artificial neural networks trained using historical data and time series analysis algorithms indicate that the number of ships departing from Samsun Port and the cargo volume will continue to increase.

Aksoy (2011) conducted a study examining the processes within Ro-Ro terminals, explicitly focusing on the procedures of trucks disembarking from ships and those arriving by road to be loaded onto Ro-Ro vessels. This investigation emphasized factors such as gamma rays used in X-ray machines, weighing scales for measuring the tonnage of trucks, areas where trucks await vessels, and loading and unloading ramps within the terminals. A simulation model was developed using the "Arena 11.0" simulation program in conjunction with these factors. The model was run repeatedly ten times over 30 days to obtain results. These outcomes led to the identification of potential problems during operations and the proposal of possible solutions. The results indicate that the current capacity of Samsun Port is sufficient. However, the existing situation should be closely monitored, and predictions should be made in advance regarding when the capacity may be exceeded to prevent potential revenue losses.

In his study, Yıldırım (2006) examined the factors influencing the development of Ro-Ro transportation and took the example of Pendik Ro-Ro Port. It was observed that Ro-Ro transportation is rapidly growing in Türkiye, and the study concluded that long-term investments are necessary in this field. Similarly to Yıldırım's work, this article also observes a rapid increase in Ro-Ro transportation at Samsun Port compared to past years. Within this context, potential additional investments for Samsun Port should be considered in the upcoming period.

6. CONCLUSION AND RECOMMENDATIONS

In this study, demand forecasting for the cargoes transported at Samsun Port's Ro-Ro terminal was conducted using time series analysis and artificial neural networks. A literature review revealed no similar research concerning Samsun Port in the context of Ro-Ro transportation, and the use of these two methods together in a single study was not observed. Therefore, with its unique approach, this study is expected to contribute to the literature significantly.

As observed in the study findings, it is estimated that there will be 84 departures from Samsun Port in December 2023. Upon examining the current structure of the terminal, it is evident that the quay can serve multiple vessels simultaneously. Therefore, there is no need for the port to develop an additional quay at its present state, given that sufficient quay space is available until December 2023. However, when the forecasting results are scrutinized, it is clear that the number of vessels is showing an increasing trend. This implies that additional investments may be necessary in the coming period. Consequently, the number of vessels handled at the port and the terminal's capacity should be closely monitored. Maintenance of the idle quays or the construction of new quays can be undertaken to increase capacity.

On the other hand, the forecasts for December 2023 indicate that the projected cargo volume for Samsun Port will remain below its current capacity. However, similar to vessel count predictions, the transported cargo volume also exhibits an increasing trend. Additionally, adverse weather conditions, when they hinder vessel entries and departures in other ports, lead to vessels departing from Samsun Port to wait in the anchorage areas of different ports, causing a buildup of vessel traffic. This situation delays the return of Ro-Ro vessels to Samsun Port. Considering these two factors, Samsun Port will require dedicated roads to port terminals and areas to accumulate trucks due to waiting to ensure smooth operation in the coming period. This situation should be closely monitored, and the necessary investments and infrastructure developments must be planned accordingly.

Future studies may encompass separate demand forecasts for each terminal at Samsun Port (general cargo, containers, liquid cargo). The impact of diversifying the input variables with different data sources on the results can be examined. Furthermore, the efficacy of varying input variables using various methods in predicting port cargo traffic can be determined. Finally, longer-term predictions can be made to ascertain when an increase in port capacity will be required.

When examining previous studies, it is observed that cargo forecasting is predominantly conducted for container terminals. A comprehensive study specifically for Ro-Ro terminals has not been encountered. Therefore, the current study is deemed to address this gap in the literature. The results obtained from the study are anticipated to fill this void and provide data that port authorities, agents, Ro-Ro operators, and individuals in the maritime sector can benefit from. It is expected that these stakeholders can reevaluate their projections for the future based on the data obtained from the study. The primary reason for selecting data between 2009 and 2021 in this study is the absence of data from other years at the port authority from which the data was obtained, posing a significant constraint in the study.

Port expansions and capacity increases should not be monitored for a certain period of time and future projection studies should be carried out regularly. In future studies, the methods used in this research can be applied to other ports. Additionally, different methods can be used for cargo forecasting in Ro-Ro transportation.

AUTHORSHIP CONTRIBUTION STATEMENT

Tayfun ŞİMŞEK: Conceptualization, Methodology, Validation, Collecting of Data, Formal Analysis, Resources, Writing - Original Draft, Writing-Review and Editing, Data Curation, Software, Visualization.

Fırat SİVRİ: Methodology, Formal Analysis, Writing-Review and Editing, Software, Visualization.

Özkan UĞURLU: Conceptualization, Methodology, Writing-Review and Editing,

Software, Visualization.
Mehmet AYDIN: Conceptualization, Methodology, Validation Formal Analysis, Resources, Writing-Review and Editing, Software, Visualization.

CONFLICT OF INTERESTS

The authors declare that for this article they have no actual, potential or perceived conflict of interests.

ETHICS COMMITTEE PERMISSION

No ethics committee permission is required for this study.

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