

Time Series Analysis and Forecasting of Turkey's Exports and Imports

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Highlights

- The forecasted results for the years 2025 to 2027 suggest an upward trend in both export and import values.
- The import growth rate is forecasted to be higher than the export growth rate.
- An expansion in the foreign trade deficit may lead to greater external dependency in the Turkish economy.

Article Info	Abstract
Article History: Received: May 13, 2025 Accepted: May 29, 2025	With the increasing impact of globalization, foreign trade has become a strategic tool, particularly for developing countries, in fostering economic growth, encouraging technological advancement, and reducing external dependency. In this context, expanding the volume of foreign trade offers various opportunities for developing economies. Accordingly, a time series-based forecasting model was developed to generate projections for Turkey's foreign trade, focusing on export and import values, using official annual trade data from 2013 to 2024. Within the scope of this study, six different statistical analysis methods were applied using Minitab 17 software. The error metrics and resulting analytical outcomes enhance the understanding of structural patterns in Turkey's foreign trade and provide strategic foresight for investment-related decision-making. Therefore, the primary aim of this study is to emphasize the importance of time series analysis in economic decision-making processes and to offer a scientific contribution to macroeconomic planning strategies.
Keywords: Export; Import; Time Series Analysis; Foreign Trade Forecasting	

Türkiye'nin İhracat ve İthalat Değerlerinin Zaman Serisi Analizi ve Tahmini

Makale Bilgileri	Öz
Makale Tarihçesi: Geliş: 13 Mayıs 2025 Kabul: 29 Mayıs 2025	Küreselleşmenin etkisinin artmasıyla birlikte, dış ticaret özellikle gelişmekte olan ülkeler için ekonomik büyümeyi desteklemede, teknolojik gelişimi teşvik etmede ve dışa bağımlılığı azaltmada stratejik bir araç haline gelmiştir. Bu bağlamda, dış ticaret hacminin artırılması, gelişmekte olan ekonomiler için çeşitli fırsatlar sunmaktadır. Bu doğrultuda, Türkiye'nin dış ticaretine yönelik ihracat ve ithalat değerlerine odaklanan bir zaman serisi tabanlı tahmin modeli geliştirilmiştir; modelde 2013–2024 yıllarına ait resmi yıllık ticaret verileri kullanılmıştır. Çalışma kapsamında Minitab 17 yazılımı aracılığıyla altı farklı istatistiksel analiz yöntemi uygulanmıştır. Hata ölçütleri ve elde edilen analiz sonuçları, Türkiye'nin dış ticaretindeki yapısal desenlerin anlaşılmasını geliştirmekte ve yatırıma yönelik karar alma süreçleri için stratejik öngörü sağlamaktadır. Bu nedenle çalışmanın temel amacı, ekonomik karar alma süreçlerinde zaman serisi analizinin önemini vurgulamak ve makroekonomik planlama stratejilerine bilimsel katkı sağlamaktır.
Anahtar Kelimeler: İhracat; İthalat; Zaman Serisi Analizi; Dış Ticaret Tahmini	

1. Introduction

The phenomenon of globalization, which began to show its influence in the 1980s, led to a significant increase in interactions among financial markets, especially during the 1990s. These developments accelerated the process of financial liberalization, resulting in more intensive capital flows between countries. The rise in capital mobility was also reflected in foreign trade data. Foreign trade fundamentally consists of exports and imports. While exports are affected by the exchange rate and the income level of the trading partner country, imports are generally associated with the exchange rate and the economic strength of the domestic country. In this regard, the direction and nature of the relationship between countries' income levels and the volume of foreign trade are noteworthy from an economic analysis perspective (Oğul, 2021). With the increasing effects of globalization, foreign trade has become a key component in national strategies for economic growth and development. Especially for developing countries, expanding the volume of foreign trade offers several opportunities, such as promoting technological advancement, increasing production capacity, and reducing financial dependency on external resources (Krugman and Obstfeld, 2009). As international integration has become more widespread, trade between nations has acquired a strategic role not only in terms of economic growth but also in fostering technological transformation and financial stability. In the case of developing economies, this indicates that outward-oriented trade policies contribute positively to multifaceted development goals.

In light of these developments, it can be stated that foreign trade not only facilitates the flow of goods and services but also contributes to the dissemination of knowledge, technology, and quality standards across countries. This interaction is particularly significant for developing economies, as it plays a vital role in enhancing competitiveness and ensuring sustainable

development. Export activities strengthen the ability of domestic firms to compete in global markets and contribute to increased investments and expanded employment opportunities through the inflow of foreign currency revenues. On the other hand, imports serve a critical function, especially in the procurement of intermediate and capital goods required during the production process (Grossman and Helpman, 1991). Nevertheless, excessive dependence on imports may lead to macroeconomic vulnerabilities such as rising current account deficits and increased external dependency (Rodrik, 2006). For this reason, maintaining a balanced relationship between exports and imports is of strategic importance for the sustainability of foreign trade policies. Accordingly, this study utilizes time series analysis methods to generate forecasts for Turkey's future export and import figures. Time series analysis enables the modeling of trends, seasonality, and cyclical fluctuations observed in economic indicators by examining structural patterns in historical data. In this regard, three fundamental techniques trend analysis, exponential smoothing, and moving average were employed to analyze time-dependent dependencies in trade data and to produce future-oriented forecasts.

Whereas trend analyses help identify the overall direction of the data over time, the exponential smoothing method provides flexibility in short-term forecasting by assigning more weight to recent observations. Moving averages, on the other hand, are used to smooth out fluctuations in the series by calculating the average of past data points, thereby revealing the underlying trend. The diversity of these techniques allows for a more comprehensive evaluation of forecasting performance. All these methods were applied using the Minitab 17 software in accordance with the structure of the data, and the results were compared in an effort to determine the most appropriate forecasting model.

1.1. Literature Review

Time series analyses are frequently employed to understand the dynamic structure of economic and financial data and to make forward-looking forecasts. To this end, the ARIMA (Autoregressive Integrated Moving Average) model developed by Box and Jenkins (1970) enables the modeling of key structural components such as trend, seasonality, and stationarity in time series. This model has been widely used in economic forecasting studies. Furthermore, the ARCH (Engle, 1982) and GARCH (Bollerslev, 1986) models, developed to model volatility, have significantly contributed to the analysis of time series with changing variance structures.

In early studies specific to Turkey, Karagöz and Doğan (2005) applied the ARIMA model to monthly export data and found it to produce successful forecasts. Similarly, Erdoğan and Bozkurt (2009) analyzed periodic fluctuations in Turkey's foreign trade values using ARIMA. Özatay, Özmen, and Şahinbeyoğlu (2007) examined the impact of exchange rate volatility on foreign trade within the framework of the J-curve hypothesis, concluding that the effect varies in the short and long term.

Aktaş (2010) focused on the relationship between foreign trade and macroeconomic indicators in Turkey and used the VAR (Vector Autoregressive) model to analyze the interactions between exports, imports, exchange rates, and the industrial production index. Similarly, Demirhan (2012) used the VECM (Vector Error Correction Model) to identify the long-term relationships affecting the trade deficit.

Bilgin (2012) emphasized the role of global demand conditions in Turkey's export forecasts and highlighted that the growth rates of major trading partners improved prediction accuracy. Aydın and Başar (2014) analyzed the volatility in Turkey's foreign trade data using the GARCH model and successfully modeled the

impact of the 2001 and 2008 crises. In the same year, Yurdakul (2014) applied Johansen cointegration tests to assess the long-run relationship between exports, imports, and economic growth, and confirmed the existence of long-term cointegration.

Aydın and Şentürk (2017) applied the ARIMA model to Turkey's foreign trade data, tested its sensitivity to seasonal effects, and reported strong forecasting performance. Akgül and Sayyan (2015) analyzed seasonality in trade data using the TRAMO-SEATS method and found that seasonal adjustment significantly improved forecast accuracy.

Moreover, machine learning-based approaches have recently been integrated into foreign trade forecasting in addition to traditional econometric models. Özmen and Sarier (2012) used Artificial Neural Network (ANN) models to predict Turkey's export data and reported superior performance compared to ARIMA. Kayakuş and Çelik (2018) employed support vector machines, decision trees, and deep learning techniques to analyze import data and demonstrated that hybrid modeling approaches enhanced predictive performance.

Kara and Duran (2020) analyzed the interactions among exchange rate, inflation, and foreign trade using a VAR model, revealing complex dynamic relationships among the variables. Uslu and Çelik (2021) compared Support Vector Regression (SVR) and ANN models, concluding that the SVR model performed better in export forecasting.

Recent studies have increasingly focused on the success of hybrid models. Erdil and Sarıkaya (2019) developed a hybrid model combining ARIMA and ANN and reported more accurate forecasts than conventional methods. Gültekin (2022) proposed a hybrid model based on ARIMA and LSTM (Long Short-Term Memory), showing that combining classical statistical techniques with deep learning

enhances forecasting accuracy. Kılıç and Yücel (2021) integrated wavelet transformation with deep learning algorithms and found that the models produced more robust results, especially during economic crises.

In conclusion, both traditional time series models (ARIMA, VAR, VECM, GARCH) and modern artificial intelligence-based approaches (ANN, SVR, LSTM) have been used in forecasting Turkey's foreign trade. In recent years, hybrid modeling methods have proven to be more successful in terms of predictive accuracy.

2. Method

2.1. The Collection of the Data

The forecasting process is an approach aimed at estimating the potential outcomes of future situations or variables based on historical and current data. Within a statistical framework, forecasting refers to the process of estimating the value of an unobservable parameter by utilizing sample data. These methods enable decision-makers to develop strategic plans for the future and to minimize the impact of uncertainties (Makridakis, Wheelwright and Hyndman, 1998).

Against this background, time series analysis commonly employed in economic and commercial decision-making processes stands out as one of the fundamental tools in forecasting studies. Time series data, which form the input of such analyses, may include components such as trends, seasonal variations, random fluctuations, and structural changes in variability over time. The primary objective of analyzing such data is to reveal the effects of unexpected events, evaluate the outcomes of known exogenous factors, and generate forecasts for future scenarios based on observed patterns (Jose, 2022).

In this scientific study, Turkey's official export and import data for the years 2013–2024 were utilized. The data were obtained from reliable institutional sources

such as the Ministry of Trade and the Turkish Statistical Institute (TÜİK). The fact that the data were organized on an annual basis enhanced the applicability of time series analysis.

2.2. Statistical Analysis

2.2.1. Trend Analysis

Trend analysis is a fundamental statistical tool used to determine the overall direction of data over time and is widely applied in economic forecasting (Makridakis et al., 1998). The trend analysis method is primarily categorized into linear and nonlinear forms. When data exhibit sudden increases or decreases, logarithmic trend models are generally preferred. In cases where there are sharp declines or significant reductions in the dataset, exponential trend analysis emerges as a more appropriate approach. On the other hand, if the dataset contains high levels of volatility, the moving average technique is employed to smooth out such fluctuations.

In linear trend analysis, it is assumed that there is a linear relationship between demand and forecast, and calculations are carried out based on this assumption. To improve the accuracy of the model, the method of least squares which aims to minimize the sum of the squared forecast errors is applied as the underlying estimation technique (Selçuk, 2019).

2.2.2. Moving Average

The primary objective of this method is to effectively reduce, to a certain extent, the influence of uncontrollable random factors on the data. A moving average forecast for a given period is typically obtained by calculating the arithmetic mean of the values from two or more preceding time intervals. The main challenge in this method lies in accurately determining the optimal value of n that provides the highest forecasting accuracy. Therefore, different n values are tested systematically, and the one that yields the lowest average deviation is selected (Kobu, 2017).

2.2.3. Single Exponential Smoothing

The simple exponential smoothing method is applied to time series that exhibit no clear trend or seasonal variation and generally fluctuate around a stable mean. Recognized as the most basic form among exponential smoothing techniques, this method smooths out random variations in the data series, providing a more structured pattern. Due to this characteristic, it stands out as a widely used and practical option among smoothing techniques (Palit and Popovic, 2006).

2.2.4. Double Exponential Smoothing

The double exponential smoothing method is a forecasting technique developed for time series data that exhibit a linear trend. This approach extends the classical single exponential smoothing by incorporating the trend component into the model. The method dynamically updates both the level and trend components for each data point, aiming to produce more accurate forward-looking forecasts (Hyndman and Athanasopoulos, 2018).

2.2.5. Error Metrics in Demand Forecasting

Evaluating the performance of forecasting models and maintaining control over the forecasting process are crucial for understanding the accuracy of the obtained predictions. Forecast errors, which represent the difference between actual demand and estimated, serve as a fundamental criterion in assessing the effectiveness of the applied method (Chase, Aquilano and Jacobs, 1998). To identify the magnitude of forecast errors, the following methods are commonly used: Mean Absolute Deviation (MAD), Mean Squared Deviation (MSD), and Mean Absolute Percentage Error (MAPE) (Şenbaş, 2020).

3. Research Methodology

The aim of this study is to contribute to the understanding of structural trends observed in Turkey's foreign trade and to provide forward-looking insights

for investors. For this purpose, seasonally adjusted import and export data were obtained from the official website of the Turkish Statistical Institute (TUIK), and Table 1 was created accordingly. These data were subjected to time series analyses. The normality of the data distribution was tested. Although the Box-Jenkins method was initially considered for demand forecasting, the dataset was found to be unsuitable for this approach.

All analyses were performed using the Minitab 17 statistical software package. A total of six different analytical techniques were applied, including trend analyses (linear, quadratic, exponential), moving average, and both single and double exponential smoothing methods.

Table 1 : Calendar adjusted external trade (2013–2025)

Years	Exports (\$ Thousand)	Imports (\$ Thousand)
2013	162 060 942	261 434 182
2014	166 355 733	251 053 870
2015	150 161 933	212 647 581
2016	149 447 343	202 443 832
2017	164 058 517	238 224 882
2018	177 069 310	230 827 155
2019	180 904 116	210 616 676
2020	168 282 952	218 153 933
2021	225 763 927	272 075 444
2022	254 110 752	362 657 106
2023	255 665 441	359 716 169
2024	261 241 644	344 564 820

4. Results

In time series analysis, particularly in classical techniques such as trend analysis, moving averages, and exponential smoothing, the assumption of normality is not a necessary prerequisite. These methods primarily aim to decompose and model the underlying structural components of the series namely trend, seasonality, and irregular fluctuations rather than relying on the statistical distribution of the raw data. Consequently, the presence of abrupt increases and

decreases does not invalidate model construction; on the contrary, such volatility can offer valuable diagnostic information for model specification. In this regard, the irregular patterns observed in Figures 1 and 2, along with the failure to meet the normality assumption, justify the use of time series modeling over classical parametric approaches such as linear regression. Time series methods are inherently designed to accommodate temporal dependencies and dynamic behavior, thereby enabling more robust forecasting performance even in the presence of non-normal and volatile data structures.

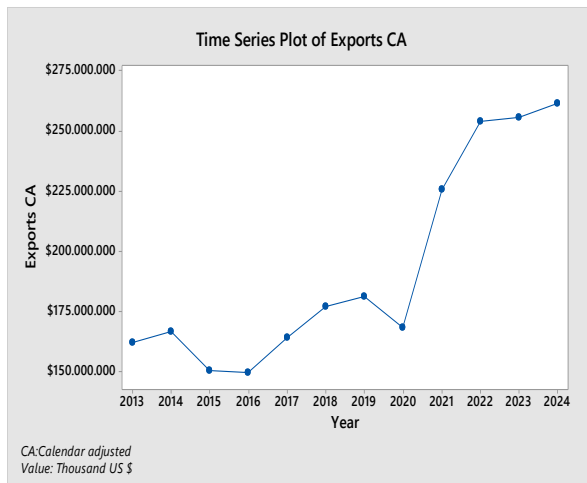


Figure 1. Time series plot of exports

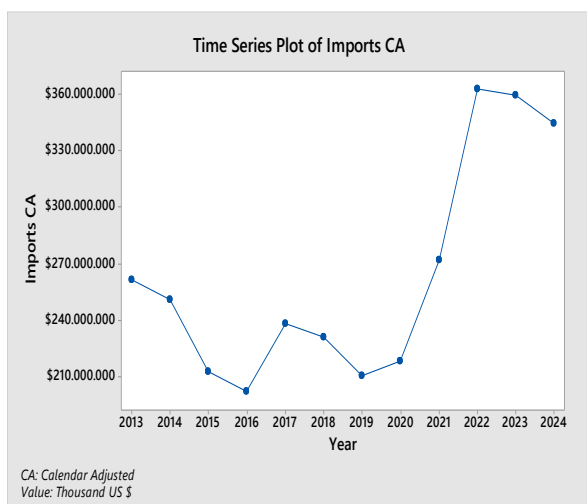


Figure 2. Time series plot of imports

4.1. Export Forecast Results

As the first forecasting method, linear trend analysis was applied. The model's forecast values were obtained from the analysis. The error metrics for this model were calculated as follows: MSD = $3.90784 \cdot 10^{14}$, MAD = $1.73783 \cdot 10^7$, and MAPE = 9.53877. The formula used in the computation is as follows:

$$Y_t = 124278978 + 10561216 \times t$$

Secondly, quadratic trend analysis was conducted. The forecast values of the model were derived, and the error metrics were calculated as: MSD = $1.66105 \cdot 10^{14}$, MAD = $0.97657 \cdot 10^7$, and MAPE = 4.97227. The corresponding equation is:

$$Y_t = 167391707 - 7915667 \times t + 1421299 \times t^2$$

Third, exponential trend analysis was performed. Forecast values were calculated, and the error metrics were found to be: MSD = $3.22699 \cdot 10^{14}$, MAD = $1.59386 \cdot 10^7$, and MAPE = 8.57257. The model formula is as follows:

$$Y_t = 134367893 \times 1.05371^t$$

Fourth, the simple exponential smoothing method was applied. Forecast values were generated, and the error metrics were: MSD = $4,24932 \cdot 10^{14}$, MAD = $1,37029 \cdot 10^7$, and MAPE = 6,82808. The smoothing constant was determined as $\alpha = 0.95$.

Fifth, the double exponential smoothing method was implemented. Forecast values were obtained, and the error metrics were as follows: MSD = $4,44396 \cdot 10^{14}$, MAD = $1,66508 \cdot 10^7$, and MAPE = 8,91226. The smoothing parameters were calculated as α (level) = 0.90 and γ (trend) = 0.10.

Finally, the moving average method was applied. Forecast values were computed, and the error metrics were: MSD = $10,3141 \cdot 10^{14}$, MAD = $2,58795 \cdot 10^7$, and MAPE = 11,8129.

4.2. Import Forecast Results

As the first forecasting method, linear trend analysis was performed. The forecast values of the model were obtained through the analysis. The error metrics of the analysis were calculated as follows: $MSD = 17.2918 \cdot 10^{14}$, $MAD = 3.6939 \cdot 10^7$, and $MAPE = 14.4628$. The equation used in the calculation is:

$$Y_t = 190742233 + 11224472 \times t$$

Secondly, quadratic trend analysis was conducted. The model's forecast values were determined. The corresponding error values were: $MSD = 6.58649 \cdot 10^{14}$, $MAD = 2.05282 \cdot 10^7$, and $MAPE = 7.60287$. The equation is given below:

$$Y_t = 284849456 - 29107194 \times t + 3102436 \times t^2$$

Third, exponential trend analysis was applied. The forecast values of the model were calculated, and the error metrics were: $MSD = 16.2517 \cdot 10^{14}$, $MAD = 3.53053 \cdot 10^7$, and $MAPE = 13.5444$. The model equation is as follows:

$$Y_t = 200385420 \times 1.0397^t$$

Fourth, the simple exponential smoothing method was implemented. The forecast values were obtained, and the error metrics were calculated as: $MSD = 13,4720 \cdot 10^{14}$, $MAD = 2,67298 \cdot 10^7$, and $MAPE = 9,93637$. The smoothing constant was found to be $\alpha = 0.95$.

Fifth, the double exponential smoothing method was used. The forecast values were derived, and the error metrics were: $MSD = 16,9231 \cdot 10^{14}$, $MAD = 3,42821 \cdot 10^7$, and $MAPE = 12,9833$. The smoothing parameters were α (level) = 0.90 and γ (trend) = 0.10.

Finally, the moving average method was applied. Forecast values were generated, and the error metrics were calculated as: $MSD = 13.4891$, $MAD = 2.6592$, and $MAPE = 9.86566$.

The analysis of import and export error rates is presented in Table 2 and 3. The table includes MSD, MAD, and MAPE values corresponding to the results of six different forecasting methods. When all error metrics are considered, it is observed that the quadratic trend analysis yields the lowest error values among the methods compared.

Table 2 : Results of error metrics for export data

Forecasting Methods Utilized	Exports		
	MAPE	MAD	MSD
Linear Trend Analysis	9.5388	$1.738 \cdot 10^7$	$3.908 \cdot 10^{14}$
Quadratic Trend Analysis	4.9723	$0.977 \cdot 10^7$	$1.661 \cdot 10^{14}$
Exponential Trend Analysis	8.5726	$1.594 \cdot 10^7$	$3.227 \cdot 10^{14}$
Single Exponential Smoothing	6.8281	$1.370 \cdot 10^7$	$4.249 \cdot 10^{14}$
Double Exponential Smoothing	8.9123	$1.665 \cdot 10^7$	$4.444 \cdot 10^{14}$
Moving Average	11.8129	$2.588 \cdot 10^7$	$10.31 \cdot 10^{14}$

Table 3 : Results of error metrics for import data

Forecasting Methods Utilized	Imports		
	MAPE	MAD	MSD
Linear Trend Analysis	14.463	$3.694 \cdot 10^7$	$17.292 \cdot 10^{14}$
Quadratic Trend Analysis	7.603	$2.0528 \cdot 10^7$	$6.587 \cdot 10^{14}$
Exponential Trend Analysis	13.544	$3.5305 \cdot 10^7$	$16.25 \cdot 10^{14}$
Single Exponential Smoothing	9.9364	$2.6730 \cdot 10^7$	$13.47 \cdot 10^{14}$
Double Exponential Smoothing	12.983	$3.4282 \cdot 10^7$	$16.92 \cdot 10^{14}$
Moving Average	9.8657	$2.659 \cdot 10^7$	$13.49 \cdot 10^{14}$

As shown in Figure 3 and 4, the forecast values that are closest to the actual import and export values are produced by the quadratic trend analysis model.

Figure 5 and 6 presents the forecast results of the quadratic trend analysis, which yielded the lowest error rates. In the graph, the blue line represents the actual values, the red line indicates the estimated from the analysis, and the green line shows the projected values for the next three years.

Following the Quadratic trend analysis, the single exponential smoothing method provided the second-best results. Compared to the quadratic trend analysis,

the MAPE difference for export data is 37.3%, and for import data, it is 30.7% in the Single Exponential Smoothing results.

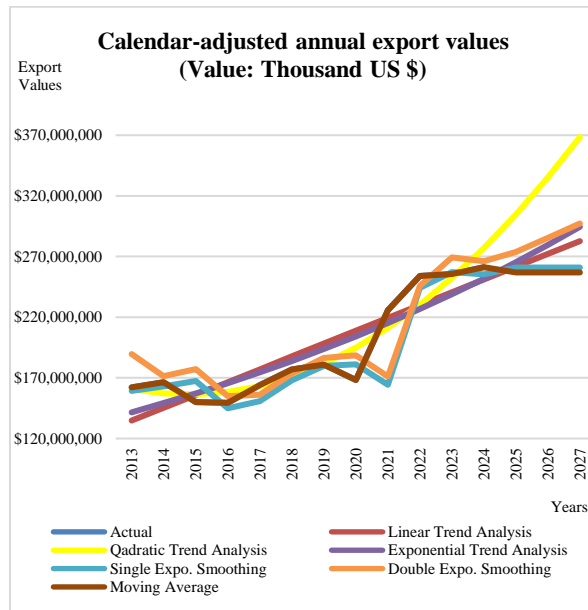


Figure 3. Calendar-adjusted annual export values

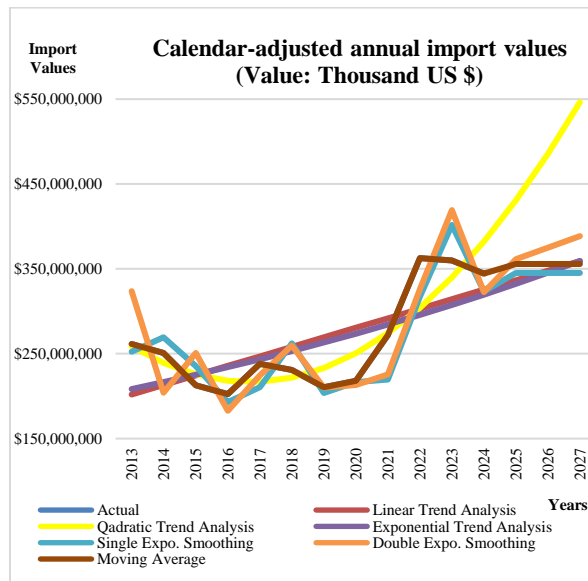


Figure 4. Calendar-adjusted annual import values

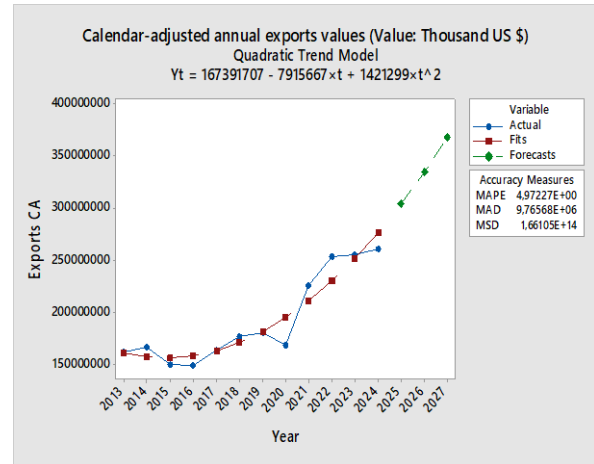


Figure 5. Forecast result of export based on quadratic trend analysis

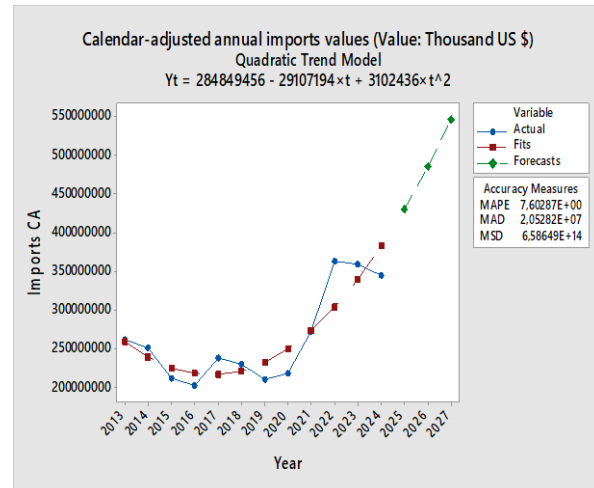


Figure 6. Forecast result of import based on quadratic trend analysis

5. Discussion and Conclusion

In this study, a comprehensive time series analysis was conducted to produce forward-looking projections of Turkey's foreign trade performance. The primary objective of the research is to evaluate the predictive capabilities of different statistical forecasting methods and to identify the model that provides the highest level of accuracy in estimating future trade volumes. For this purpose, annual foreign trade data for the period 2013–2024 were obtained from the Turkish Statistical Institute (TÜİK), forming the empirical basis of the analysis.

Using Minitab statistical software, six different time series forecasting methods were applied: linear trend analysis, quadratic (second-degree) trend analysis, exponential trend analysis, single exponential smoothing, double exponential smoothing, and the moving average method. These methods were applied to historical data to generate three-year forecasts for the period 2025–2027.

As a result of the analysis, the actual and estimated for exports and imports were systematically compared and presented in Table 4. This structured approach helped identify the most accurate forecasting method and provided a basis for making evidence-based economic and policy insights about the future of Turkey's foreign trade.

Table 4. Comparison between forecast results and actual values

Years	Exports		Imports	
	Actual	Quadratic Trend Analysis	Actual	Quadratic Trend Analysis
2013	\$162 060 942	\$160 897 338	\$261 434 182	\$258 844 697
2014	\$166 355 733	\$157 245 567	\$251 053 870	\$239 044 811
2015	\$150 161 933	\$156 436 394	\$212 647 581	\$225 449 796
2016	\$149 447 343	\$158 469 817	\$202 443 832	\$218 059 653
2017	\$164 058 517	\$163 345 839	\$238 224 882	\$216 874 382
2018	\$177 069 310	\$171 064 457	\$230 827 155	\$221 893 982
2019	\$180 904 116	\$181 625 674	\$210 616 676	\$233 118 455
2020	\$168 282 952	\$195 029 487	\$218 153 933	\$250 547 799
2021	\$225 763 927	\$211 275 899	\$272 075 444	\$274 182 015
2022	\$254 110 752	\$230 364 907	\$362 657 106	\$304 021 103
2023	\$255 665 441	\$252 296 514	\$359 716 169	\$340 065 063
2024	\$261 241 644	\$277 070 717	\$344 564 820	\$382 313 894
2025		\$304 687 519		\$430 767 597
2026		\$335 146 917		\$485 426 172
2027		\$368 448 914		\$546 289 619

Value: Thousand US \$

To determine which forecasting method provides more accurate results, it is essential to examine the associated error rates. Table 2 and 3 presents the MSD, MAD, and MAPE values, which are commonly used to evaluate

forecast accuracy across the applied analytical methods. When analyzing the percentage error rates (MAPE), the Quadratic Trend Analysis stands out as the most accurate method, with the lowest MAPE values of 4.973 for exports and 7.603 for imports.

In addition to the six forecasting methods applied, the Box-Jenkins approach was also tested. However, this method was found to be unsuitable for the dataset used in this study. Based on the results, it can be concluded that future forecasts made using the Quadratic Trend Analysis method are likely to yield more reliable outcomes.

In conclusion, when examining the forecast results for the period 2025–2027, both export and import values are projected to increase. Yet, a more detailed analysis reveals that the growth rate of imports is expected to exceed that of exports. This situation may negatively impact the foreign trade balance and contribute to an increase in the current account deficit. A widening trade deficit could, in turn, intensify Turkey's dependency on external economies. Encouraging the substitution of imported raw materials and intermediate goods with domestic alternatives could help reduce external dependency and lower production costs. Given these findings, it is important for the government to implement metrics that discourage excessive imports and promote exports.

Conflict of Interest: The authors declare that there is no conflict of interest to disclose.

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