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Predictive analysis of trade flows: A lever for optimizing financial performance and adapting international marketing strategies

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Abstract: This article presents a comprehensive analysis and forecast of Tunisia's export flows in the mechanical and electrical sectors, focusing on improving predictive accuracy through time series modeling. The study began with the collection and preprocessing of historical export data, ensuring data quality and appropriate formatting for time series analysis. After exploring data to understand trends and seasonality, two classical forecasting models, ARIMA and Holt-Winters, were implemented. Due to the absence of actual export data for 2025, a model evaluation was carried out on the 2024 data, allowing an out-of-sample validation to objectively assess predictive performance. Metrics such as mean absolute error (MAE), root mean squared error (RMSE), and coefficient of determination (R^2) were calculated to compare the precision of the models. The ARIMA model demonstrated superior performance with lower MAE and RMSE values and a better R^2 score, suggesting it is better suited for capturing the patterns in the export data. The article also discusses the challenges encountered, including data frequency issues and model parameter tuning. These findings provide actionable insights for stakeholders aiming to optimize export strategies and adapt to market fluctuations. The methodology and results lay the groundwork for future work integrating machine learning techniques to further enhance forecasting capabilities.
Keywords: *ARIMA model, Economic forecasting; Export forecasting; Holt-winters method, International marketing strategy, Machine learning integration, Mechanical and electrical sector, SARIMA, Time series analysis, Trade policy, Tunisian trade.*

1. Review Literature

Forecasting export trends plays a vital role in guiding economic planning and developing targeted international marketing strategies. In this context, time series forecasting models such as the Autoregressive Integrated Moving Average (ARIMA) and Holt-Winters exponential smoothing are widely used for their accuracy and flexibility.

Nguyen and Pham [1] investigated the application of the ARIMA model to forecast Vietnam's black pepper export prices to the U.S. market. Their study demonstrated ARIMA's effectiveness in capturing both trend and seasonal fluctuations, providing valuable insights for pricing decisions and market planning. Similarly, Hasibuan, et al. [2] compared SARIMA and Holt-Winters exponential smoothing methods to forecast West Sumatra's export data. They found that Holt-Winters performed particularly well for datasets with strong seasonal components, while SARIMA offered better flexibility for longer-term trends. These findings support the use of both models in forecasting export dynamics in complex industrial sectors like mechanical and electrical engineering.

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A broader comparative study by Ersöz, et al. [3] analyzed the forecasting performance of ARIMA, Holt-Winters, and Prophet models using European COVID-19 data. While the context was health-related, the methodology revealed useful insights: ARIMA performed better with trend-dominated data, whereas Holt-Winters showed strong performance for short-term seasonal patterns. This suggests that combining the two models, as done in the present study, can enhance forecast reliability.

In terms of sectoral relevance, Kamsyakhan, et al. [4] developed an ARIMA-based model to forecast Thailand's automotive parts demand in foreign markets. Their findings emphasized how accurate forecasting can support inventory control, trade negotiation, and targeted promotional strategies. Similarly, Santi, et al. [5] applied a SARIMA model to Indonesia's oil and gas import data, highlighting the need for adaptive forecasting methods that account for market seasonality and policy influences. Beyond methodology, strategic perspectives are increasingly integrated into forecasting research. Shevchuk and Fedulova [6] explored structural changes in Ukraine's mechanical engineering exports, demonstrating how international political and economic shifts affect export performance. Their findings underscore the importance of aligning forecasting insights with adaptive marketing and industrial strategies in sectors exposed to global volatility.

A more policy-oriented study by Ščeulovs and Gaile-Sarkane [7] examined the role of forecasting and economic modeling in supporting foreign market entry and international business development. They argued that accurate forecasts empower firms to allocate resources more efficiently, tailor marketing campaigns to specific regional trends, and respond proactively to global demand shifts. This reinforces the added value of linking statistical forecasting with actionable marketing insights, which is a central aim of the present research.

In summary, the literature confirms the robustness of ARIMA and Holt-Winters models in export forecasting across various sectors and contexts. Moreover, it highlights the strategic importance of using forecasts to guide international marketing decisions, optimize export operations, and respond to structural or policy-related trade challenges. Building on these contributions, this article forecasts Tunisia's mechanical and electrical exports for 2025 using ARIMA and Holt-Winters models, with the objective of informing and strengthening international marketing strategies, in this context, we are trying to address the following problematic:

How can forecasting Tunisian exports in the mechanical and electrical sector for 2025 using statistical models help to identify possible variations from 2024 and generate suitable marketing suggestions to optimize international financial performance? Based on the literature review, we propose the following hypotheses:

H_1: The SARIMA model will outperform Holt-Winters in forecasting mechanical and electrical exports due to its ability to capture complex trends and seasonality.

H_2: Accurate export forecasts will enable firms to implement more effective international marketing strategies

2. Methodology

The data used in this article comes from the National Institute of Statistics (INS). It is a chronological time series that spans from January 2010 to December 2024 and contains monthly export values from Tunisia's mechanical and electrical sector. The dataset includes four main variables: the data: general exports referring to Tunisian enterprises that export aboard and pay Tunisian taxes ; offshore exports representing foreign enterprises operating in Tunisia and exporting aboard ; and finally ,total exports , which is the sum of both general and offshore exports.

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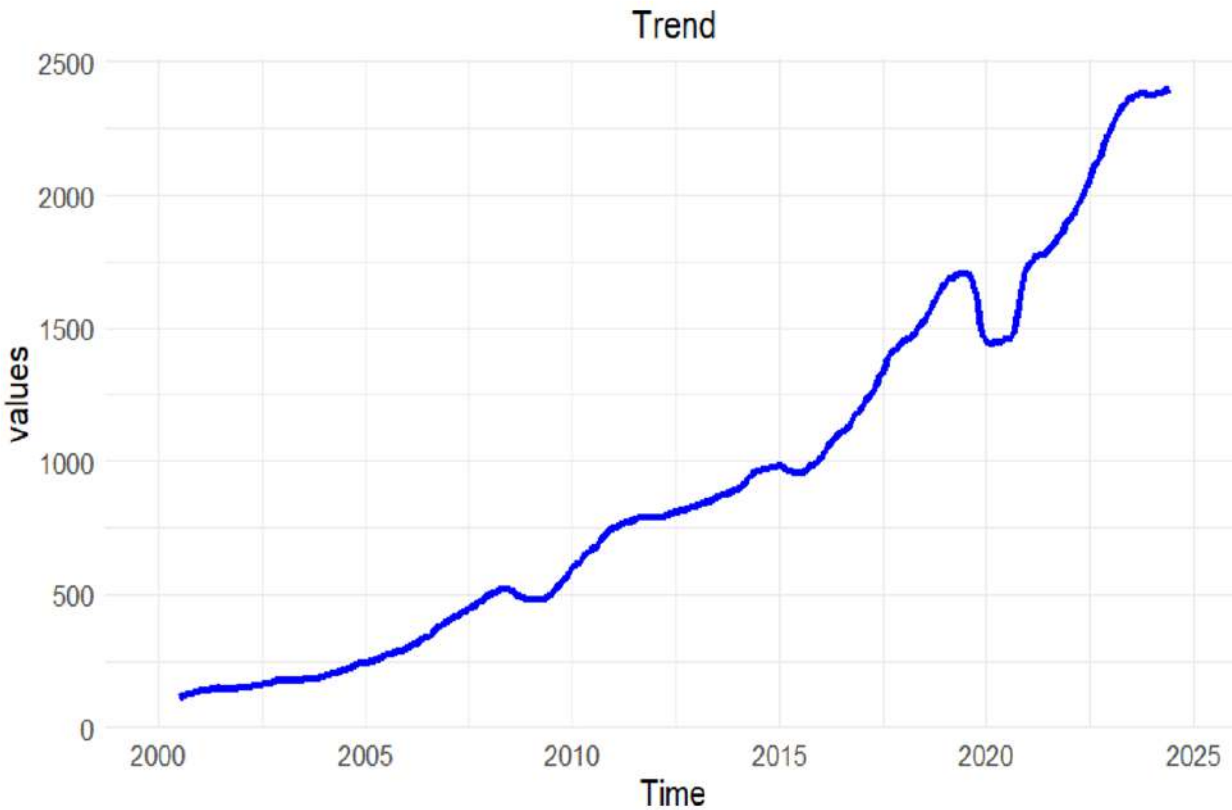

Figure 1.
Monthly export values of Tunisia's mechanical and electrical sector (2010–2024) by export type: general, offshore, and total exports.

2.1. Justification of Data Selection

The dataset was chosen for several compelling reasons. First, it is sourced from the National Institute of Statistics (INS), ensuring that the data is official, reliable, and nationally representative. Second, the monthly frequency and extended time span (2010–2024) make it suitable for applying advanced time series forecasting models such as SARIMA and Holt-Winters, which require long and stable chronological series to detect trends and seasonal patterns. Third, the dataset distinguishes between general and offshore exports, allowing for a more nuanced analysis of Tunisia's mechanical and electrical export performance. This level of detail supports the study's goal of generating actionable marketing insights tailored to different types of exporting enterprises (domestic vs. foreign). Finally, focusing on this sector aligns with Tunisia's strategic economic goals, where mechanical and electrical exports represent a key contributor to trade and industrial growth, making it a relevant and high-impact area for forecasting and strategic recommendations.

2.2. Time Series Definition

A time series is a sequence of quantitative data that reflects the variation of a certain quantity over time, typically used to analyze its historical trends and forecast its future behavior.

2.3. Components of a Time Series

2.3.1. Trend

Is a long-term movement in a data set, whether time series data in which the trend indicates that the data are increasing, decreasing, or remaining constant. This describes a long-term elastic,

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distinguishing it based on the structural movement in the data, whether it be economic growth, technological progress, or shifts in consumer behavior. Long-term trends are important for forecasting and strategic planning to allow decision makers to understand the big picture but also to look past short-term volatility.

A cycle is a long-term, nonseasonal fluctuation in economic activity that does not follow a fixed calendar pattern and can last several years, helping businesses anticipate economic changes and plan accordingly. Economic cycles include Kondratieff long waves (40–60 years), Kuznets cycles (15–25 years), Juglar business cycles (5–11 years), and Kitchin minor cycles (around 3.3 years), each reflecting different phases of investment and growth patterns. These cycles provide critical insights into the economic environment and are widely studied to improve forecasting and risk management.

2.4. Graphical Analysis

Purpose and Use: Graphical analysis is the core of the time series study, as it allows visualization of the underlying characteristics of the data, including trend, seasonality, breaks and outliers. It is important to observe the general behavior of the series via graphical display before selecting or fitting a statistical model. This step helps guide methodological decisions, emphasize potential issues, and improve the interpretation of results.

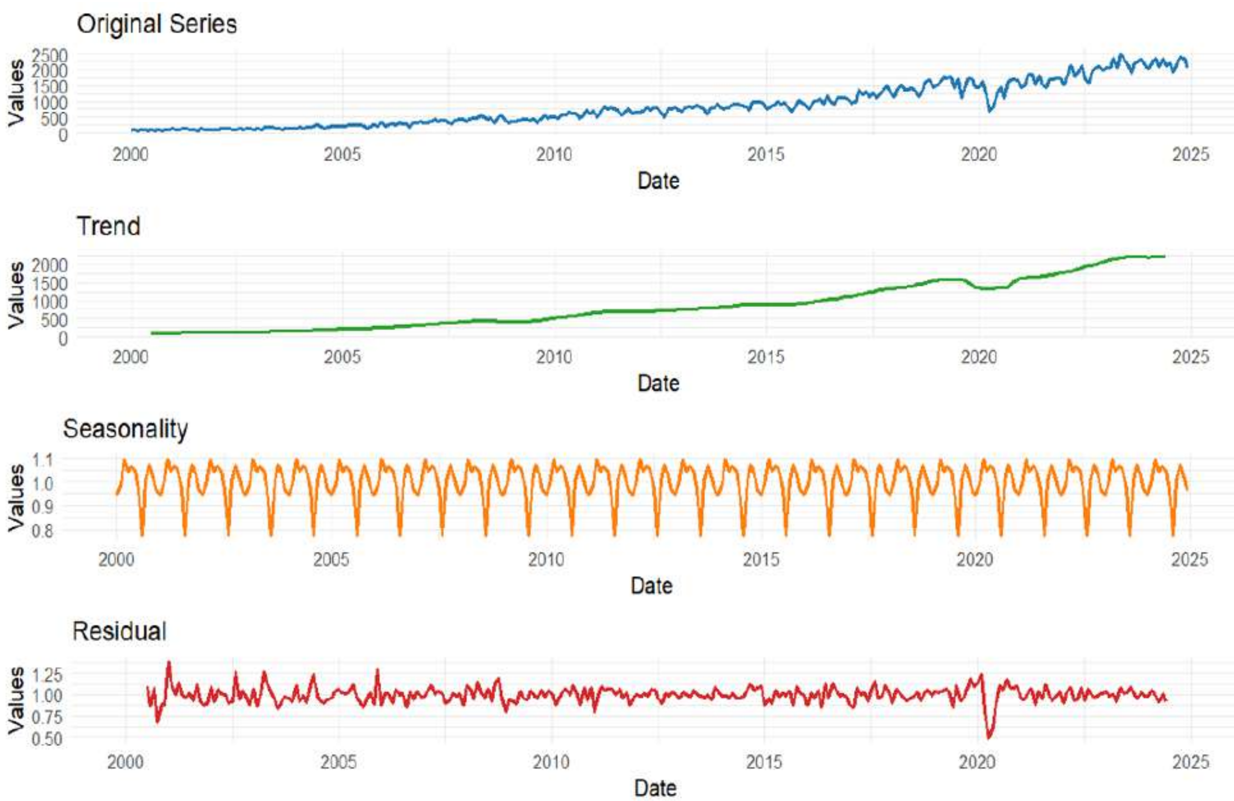

Figure 2.
Multiplicative Offshore Time Series Model.

Time Series Decomposition: To study the structure of a time series, it is important to know how its main components - the trend, seasonality, and irregular variations of each of them are combined, as this interaction determines whether the series should be modeled using an additive model or a multiplicative model. In our time series analysis, we will use the multiplicative model:

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This figure illustrates the multiplicative decomposition of offshore export data from 2000 to 2024. The original series is broken down into three main components: First, there is the trend that shows the overall upward movement over the years, and we can also see an inflection point around the 2019-2020 period. Next, we have the seasonal component that captures regular patterns that repeat each year. Lastly, there is the residual component that shows short-term variations that do not follow a pattern.

3. Forecasting

3.1. Forecasting Concepts

Forecasting is the process of making projections about future events, trends, or actions based on the study of past and present data. Forecasting is widely used in most fields, such as economics, finance, business and supply chain management, to allow planning, decision-making, and strategy development.

3.1.1. Forecasting Models

Naive methods are simple forecasting techniques that assume the future will mirror the past, ignoring trends and seasonality. Examples include naive forecasting (using the last observed value), seasonal naive forecasting (using the last value from the same season), and moving average (predicting based on the average of recent data).

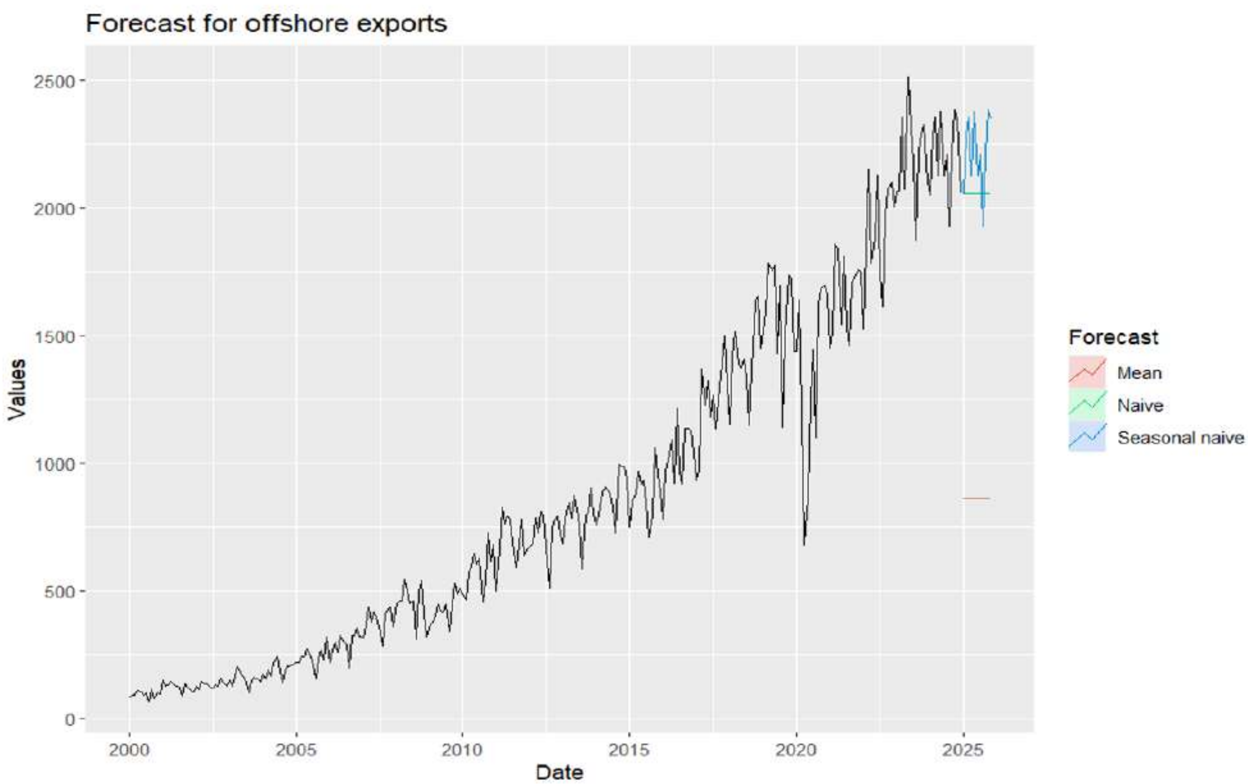

Figure 3.
Forecasts of Offshore Exports of Tunisia.

Exponential smoothing methods: forecast future values by weighting past observations with exponentially decreasing weights, giving more importance to recent data. Simple exponential smoothing suits data without trend or seasonality, Holt's linear trend extends this to capture linear trends, and Holt-Winters further incorporates seasonality by modeling level, trend, and seasonal

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components with three smoothing parameters.

The ARIMA model (Auto Regressive Integrated Moving Average) is a powerful and widely used time series forecasting method that captures trends and short-term dependencies by combining three components: autoregression (AR), moving average (MA), and integration (I) for stationarity. It models data by using past values, past errors, and differencing to remove trends, characterized by parameters (p, d, q). ARIMA is especially effective for stationary time series without persistent seasonality, making it valuable in economic and financial forecasting.

3.2. The SARIMA Model

SARIMA (Seasonal Auto Regressive Integrated Moving Average) is an extension of the ARIMA model designed to handle time series data with seasonal patterns by incorporating seasonal autoregressive, differencing, and moving average components alongside the non-seasonal parts. It models both short-term and long-term dependencies, capturing repeated patterns over fixed periods such as months or years. Represented as SARIMA (p, d, q) (P, D, Q) s, it is widely used for accurate forecasting of data exhibiting trend and seasonality.

3.3. Outlier Detection and Treatment

Forecasting models and time series analysis results can be severely affected by outliers. To increase the forecast accuracy, it is essential to recognize and handle these outliers properly.

This part describes the methods for spotting outliers and the approaches used to reduce their consequences.

3.3.1. Definition of Outliers

Outliers are data points that significantly deviate from the typical pattern of a time series, caused by factors like measurement errors, process changes, or external events. One common type is the Additive Outlier (AO), which represents isolated anomalies such as strikes or extreme weather, usually reflected in the irregular component of decomposition models.

Level shift (LS) is a permanent change in the mean level of a time series, often caused by structural changes like data reclassification. In contrast, a transitory shock is a temporary disturbance where the series gradually returns to its original level, modeled by both its magnitude and a decay period reflecting the fading effect over time.

3.3.2. Outlier Detection

Outlier detection is recognizing data that differs considerably from the main pattern of time series. There are two basic methods used: visual inspection via graphical analysis and statistical tests such as the Z-Score method, the Inter quartile Range (IQR) method, and model residual analysis.

3.3.3. Visual Inspection

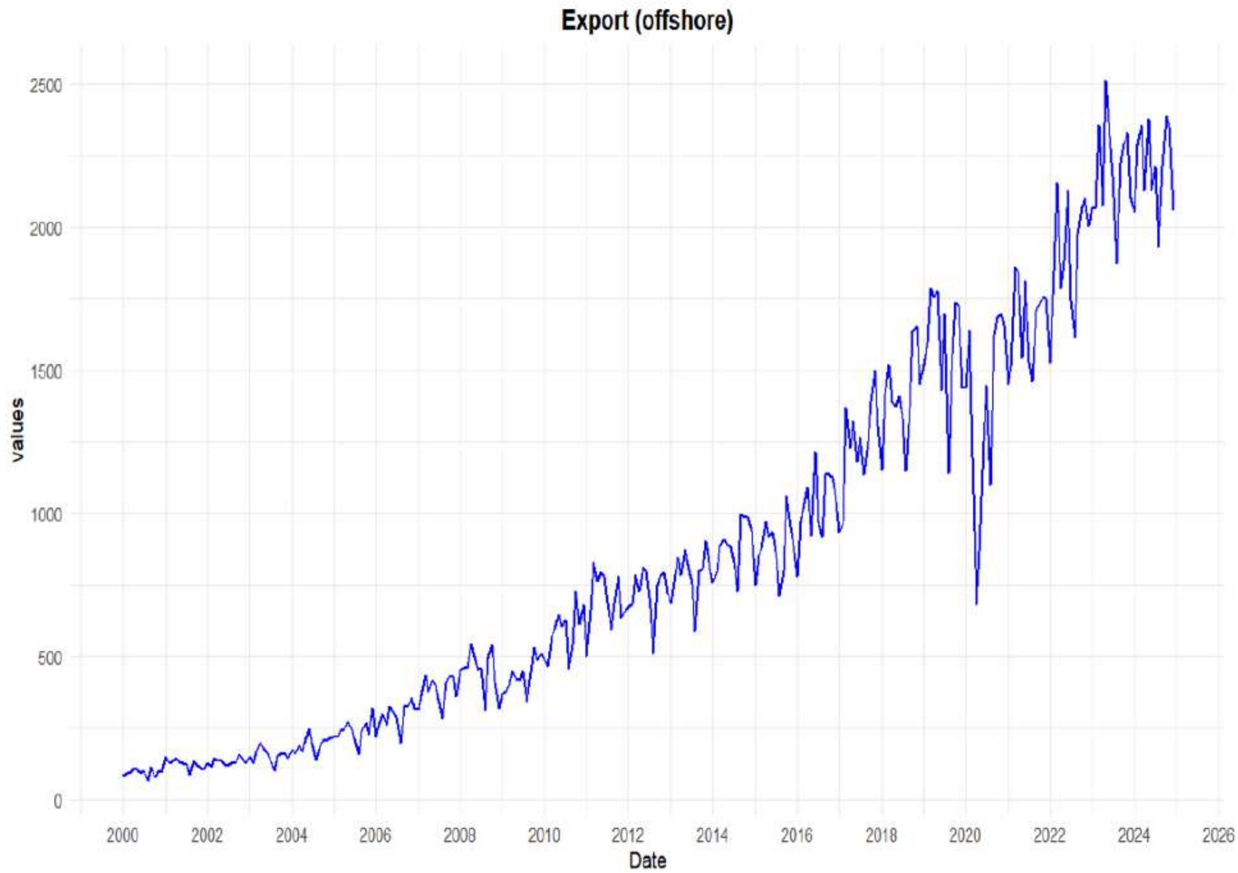

Figure 4.
Offshore Exports Graph.

Interpretation: This time series shows the overall upward trend in total exports between 2000 and 2024 with noticeable seasonal oscillations, As we can also see an inflection point around the 2019-2020 period, indicating a noticeable change in the slope of the trend; Before 2020, the slope is positive and steady, reflecting stable export growth; Around 2020, the curve flattens, suggesting a slowdown, and after 2021 the trend begins to rise again slightly. Likely corresponding to external shocks such as the COVID-19 pandemic.

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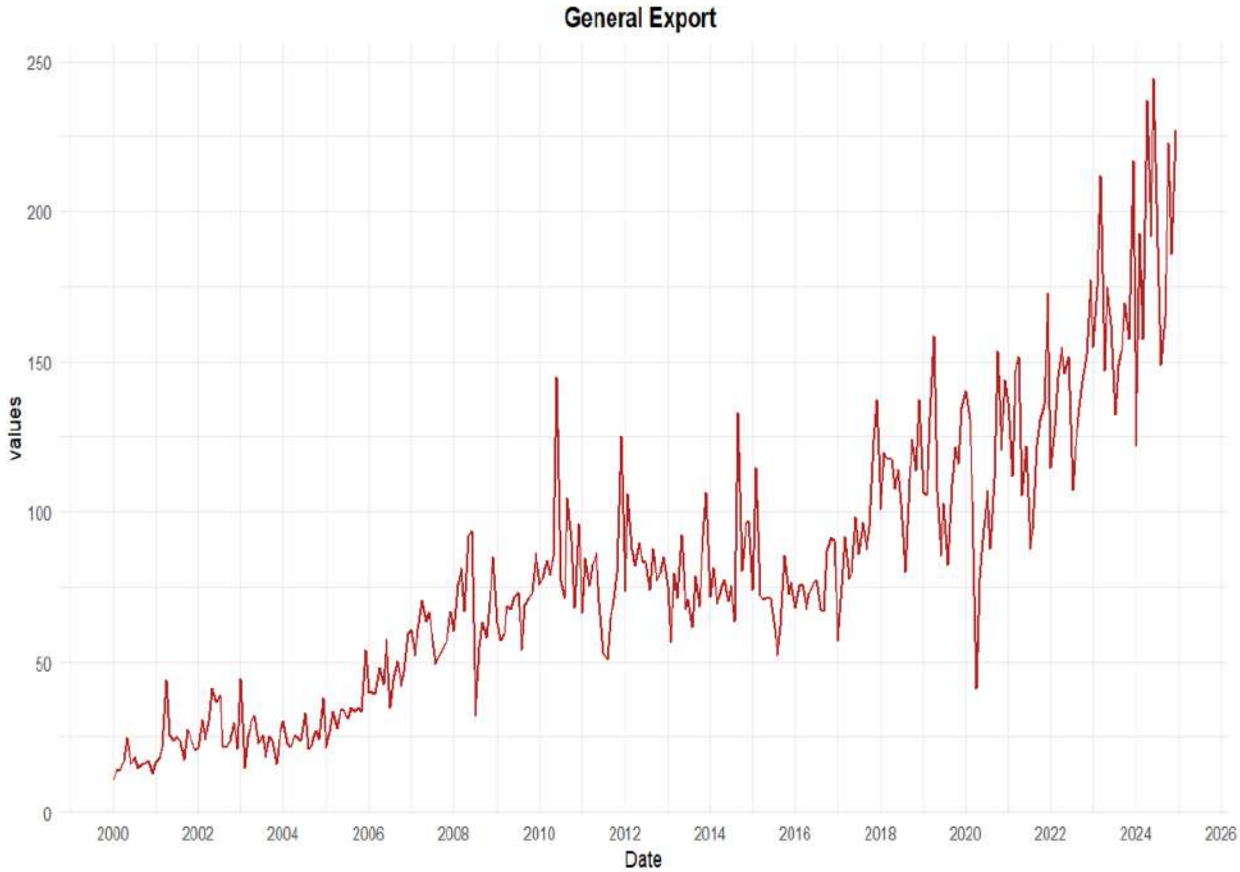

Figure 5.
General Exports Graph.

Interpretation: The time series graph of general exports clearly shows an upward trend over the years, indicating that export levels have generally increased since 2000. However, several sharp peaks and sudden drops interrupt this trend, suggesting the presence of outliers. For example, a significant drop is observed around 2020, which can likely be attributed to the impact of the COVID-19 pandemic on international trade. Similarly, some unusually high spikes appear around 2010 and again in recent years (2023-2024), deviating from regular seasonal fluctuations.

3.4. Statistical Tests

Z-Score Method: We will now use the Z-Score method for outlier detection on the offshore time series and observe that this method proves to be unreliable.

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```
#z_score calculation
z_scores <- scale(data$`exportation ( off shore)`)

#Detection threshold
outliers_zscore <- which(z_scores > 2)

#Display outlier indice
outliers_zscore
```

```
#z_score calculation
z_scores <- scale(data$`exportation ( off shore)`)

#Detection threshold
outliers_zscore <- which(z_scores > 2.5)

#Display outlier indice
outliers_zscore
```

```
> #Detection threshold
> outliers_zscore <- which(z_scores > 2)
> #Display outlier indice
> outliers_zscore
[1] 279 281 282 285 286 287 290 291 293 295 297 298 299
```

```
> #Detection threshold
> outliers_zscore <- which(z_scores > 2.5)
> #Display outlier indice
> outliers_zscore
integer(0)
```

Figure 6.
Test with z-score.

Interpretation: When we used the Z-Score method on the offshore export series, a threshold of 2 gave too many outliers, even for points that looked normal. But when we increased the threshold to 2.5, it gave no outliers at all. The big drop in 2020 wasn't detected in either case. This is because increasing the threshold makes the method stricter it only flags values that are very far from the average. As a result, the method missed important changes and is not suitable for this kind of time series.

3.5. IQR (Inter-Quartile Range) Method

```
#calculate quartiles
Q1 <- quantile(data$`exportation ( off shore)`,0.25)
Q3 <- quantile(data$`exportation ( off shore)`,0.75)
IQR_value <- Q3 - Q1

#Thresholds
lower_bound <- Q1 - 1 * IQR_value
upper_bound <- Q3 + 1 * IQR_value

#Detect outliers
outliers_iqr <- which(data$`exportation ( off shore)`< lower_bound | data$`exportation ( off shore)`> upper_bound)

#Display indice
outliers_iqr
```

```
> #calculate quartiles
> Q1 <- quantile(data$`exportation ( off shore)`,0.25)
> Q3 <- quantile(data$`exportation ( off shore)`,0.75)
> IQR_value <- Q3 - Q1
> #Thresholds
> lower_bound <- Q1 - 1 * IQR_value
> upper_bound <- Q3 + 1 * IQR_value
> #Detect outliers
> outliers_iqr <- which(data$`exportation ( off shore)`< lower_bound | data$`exportation ( off shore)`> upper_bound)
> #Display indice
> outliers_iqr
[1] 281
```

Figure 7.
Test with IQR.

Interpretation: In this analysis, the IQR method was applied with the standard threshold of -1 and +1 times the IQR to detect outliers. However, this method only identified a single data point as an outlier. This approach did not detect the most significant outlier of 2020, which was crucial for understanding the overall trend. The failure to identify this key outlier suggests that the IQR method, using this threshold, may not be the most effective for capturing critical outliers.

Given the limitations of the z-score and IQR method in detecting significant outliers, particularly the key outlier of 2020, a more robust approach is required for accurate identification of influential data points. In this regard, SARIMA (Seasonal Auto Regressive Integrated Moving Average), a time series forecasting method, provides a more effective tool. By analyzing the residuals of the SARIMA model, which represent the differences between the predicted and actual values, we can better identify discrepancies that may indicate outliers.

3.6. SARIMA Residuals

To identify true anomalies in time series data, we must first remove typical patterns like trend and seasonality. These patterns are effectively captured by SARIMA models. Once the SARIMA model is fitted to the data, the residuals (the difference between the model's

predictions and the actual data) represent the information that the model couldn't predict. These residuals can then be analyzed to detect statistical anomalies. In this analysis, we extract the residuals from the SARIMA model and apply the Z-Score approach to identify significant deviations, or outliers, that may indicate unusual or unexpected behavior in the data. This will allow us to detect and investigate anomalies in both series effectively.

Interpretation: To check if there were any unusual values in the time series, we looked at the residuals from a SARIMA model. We started by using the auto.arima () function to automatically choose the best seasonal ARIMA model for the exportation (off shore) data. Once the model was fitted, we got the residuals, which are the differences between the actual values and the values predicted by the model. To make it easier to spot unusual residuals, we calculated their Z-scores using the scale () function. A Z-score tells us how far a value is from the average, in terms of standard deviations. We then set a threshold of 3, meaning we considered any residual with a Z-score higher than 3 or lower than -3 to be an outlier. This is because in most normal distributions, nearly all values fall within three standard deviations from the mean. Finally, we used the which () function to find the positions of these outliers in the data. This helped us identify values that might be errors or events that the model couldn't explain. We identified several outliers in the residuals, including those at indices 236 , 243 , 244 , 281 which correspond to the dates 2019-08-01", "2020- 03-01","2020-04-01" , "2023-05-01" respectively.
And we will do the same thing to the general exportation data

3.6.1. Outlier Treatment

Once we have finished the detection of outliers, it is essential to treat them to avoid affecting the quality of the forecast. In this analysis, we focus on the exportation (off shore) series and apply outlier treatment methods to improve model performance and we can use as methods: smoothing , explicit modeling (indicator variable) , and post-processing validation.

3.6.1.1. Smoothing

The red segments in the graph point out the original outlier values, while the blue line shows the corrected series after local smoothing and since only a few values were changed, the two curves essentially overlap, except for the observed anomalies.

Interpretation: The code begins by specifying the positions of detected outliers in the export time series using the vector outliers-indices. To preserve the original data, a copy of the series exportation (offshore) is created and stored in the variable smoothed-series. a for loop used to go through each number in the list of outlier positions. For each one, it checks if the outlier is not at the very beginning or very end of the series (because there would be no value before or after to use). If it's safe, the outlier value is replaced with the average of the value before and the value after it. This way, we fix the strange (abnormal) values gently, without changing the general shape or trend of the data too much. The corrected series is then added to the dataset under the name exportation(offshore)-corrected. Finally, both the original and corrected series are plotted using ggplot2. The original values are shown in red and the corrected values in blue, allowing for a clear visual comparison.

3.6.1.2. Post-Processing Validation

3.6.1.2.1. Outlier Detection and Visualization: (Appendix 1)

Interpretation: First, the code creates a time series object named serie from the column exportation (off shore) in the dataset, specifying that the data starts in January 2000 with monthly frequency. Then, it plots this original time.

series to visualize any potential anomalies. Next, the tso() function from the tsoutliers package is applied to the series to automatically detect three types of outliers: Additive Outliers (AO), Level Shifts (LS), and Transient Changes (TC). The function returns an object res which contains the detected outliers and an adjusted version of the series where outliers are corrected. This adjusted series is extracted into serie_corrigee. For easier plotting, both the original and corrected series are combined into a data frame df along with their corresponding dates. Finally, the results of the outlier detection stored in res are printed and visually plotted to provide detailed information about the detected outliers and model diagnostics. (Appendix 2).

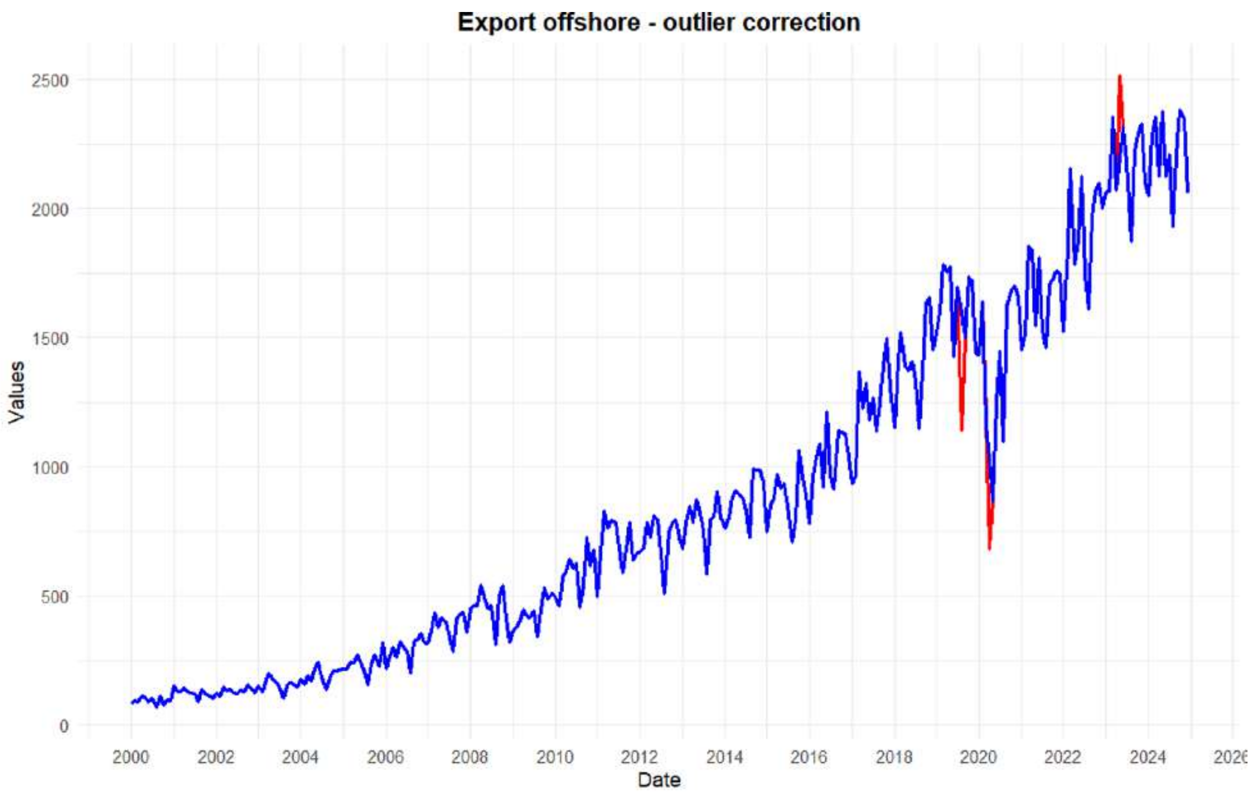

Figure 8.
Outlier Correction in Offshore Export Time Series.

Interpretation: The estimated coefficients are all statistically significant. For example, the MA(1) coefficient is -0.7636 and the seasonal AR(1) is 0.6679, both with very small standard errors, indicating stable estimation. For each outlier, a t-statistic was provided to test its statistical significance. These t-statistics come from a t-Student distribution and measure how strongly each outlier deviates from the expected behavior of the series. In this case, all the detected outliers had |t-stat| > 3, indicating that they are statistically significant and should be corrected. For example, the outlier at April 2020 (TC) had a large negative effect (-756.9) with a t-statistic of -12.079, strongly confirming its abnormal nature.

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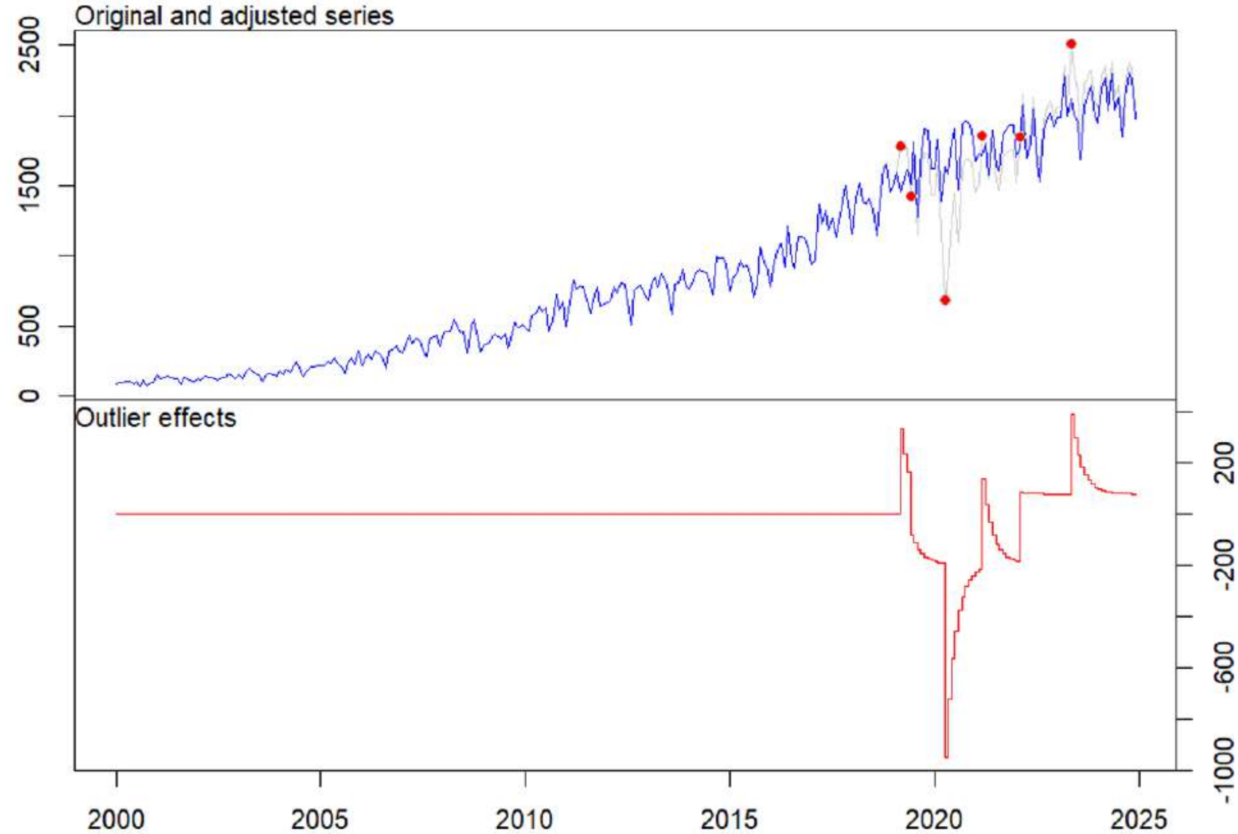

Figure 9.
Offshore Export Series with Outliers Marked.

Interpretation: The graph presents the results of an outlier detection and adjustment procedure applied to a time series of export data. The top panel compares the original series (in black) with the adjusted series (in blue), where several outliers—marked by red dots—are identified, particularly from 2018 onwards. These outliers correspond to unusual deviations likely caused by external shocks, such as the COVID-19 pandemic. The adjusted

series smooths these anomalies, offering a clearer view of the underlying trend and seasonal patterns. The bottom panel illustrates the magnitude and nature of the outlier effects. It reveals the presence of Additive Outliers (AO), which represent isolated spikes or drops, as well as Temporary Changes (TC), where the effect diminishes gradually over time. These corrections were especially prominent around 2020, reflecting short-term disruptions. By adjusting for these outliers, the series becomes more stable and suitable for accurate modeling and forecasting.

3.6.2. Post-Processing Statistical Validation

```
fit_corrected <- auto.arima(serie_corrigee, seasonal = TRUE)

checkresiduals(fit_corrected)

Box.test(residuals(fit_corrected), type = "Ljung-Box")

AIC(fit_corrected)
```

Figure 10.
R code for post-processing validation.

Interpretation: A SARIMA model was fitted to the corrected series using auto.arima(). The checkresiduals() plot showed whether the residuals looked random. The Ljung-Box test checked if the residuals were independent. A high p-value means the model is appropriate. The AIC value was used to check the model quality the lower it is, the better the model fits. (Appendix 3).

Interpretation: After correcting the outliers, the fitted SARIMA model showed significantly improved performance. The AIC value decreased from 3701.612 before correction to 3517.498 after correction, indicating a better model fit. Furthermore, the Ljung-Box test applied to the residuals of the corrected model yielded a p-value of 0.9189, which is above the 0.05 threshold, suggesting that the residuals are statistically indistinguishable from white noise. In contrast, the initial model had a p-value of 0.0158, indicating significant residual autocorrelation. These results confirm that detecting and correcting the outliers allowed us to obtain a more robust and reliable model for forecasting.

3.7. Preprocessing and Transformation of Data

3.7.1. Achieving Stationarity: Definitions and Transformation Steps

3.7.1.1. Definition of a Stationary Series

A time series is said to be stationary when its statistical properties, such as mean and variance, remain constant over time. Visually, a stationary series exhibits no apparent trend or seasonal variation.

3.7.2. Stationnarization Methods

Various transformation strategies can be used, based on the properties detected, to make a time series stationary: As mentioned above, before we can build a model, we must ensure that the time series is stationary.

Interpretation: This code is used to extract the p-value of the Dickey- Fuller test for the series, if it is less than 0.05, the series is considered stationary. According to the results provided, the time series is nonstationary because the p-value of 0.4122 is above the 0.05 significance level. (Appendix 4).

Interpretation: The code presented here performs first-order differentiation and graphical visualization of the offshore exports time series to analyze its evolution. In the second line of the code, the diff () function calculates the simple differentiation (order 1). Then the plot function draws a curve to see if the series is stationary.

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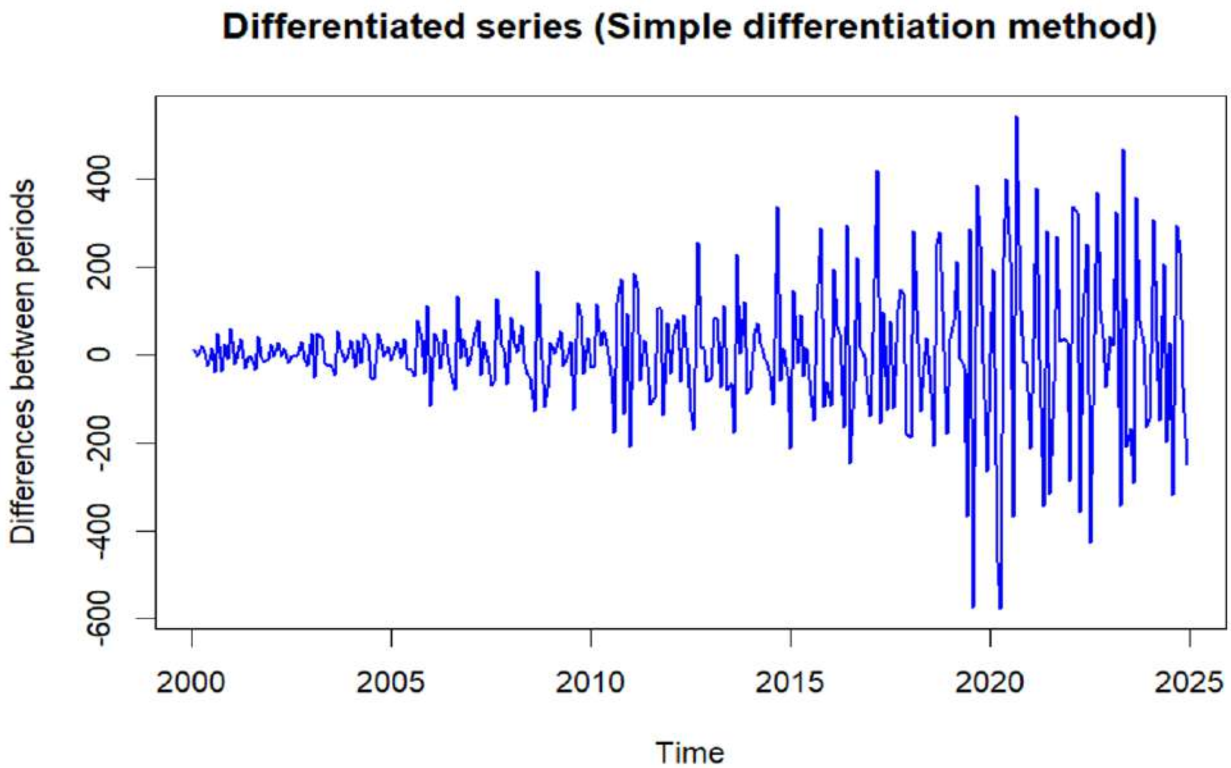

Figure 11.
Evolution of Offshore Exports per year.

Interpretation: Visually, the series fluctuates around a constant mean (the values in the series stay around the same level over time) close to zero, which suggests that the differencing was effective in removing long-term trends. However, the amplitude of fluctuations increases significantly over time, particularly from 2015 onward, indicating the presence of heteroskedasticity (non-constant variance). This means that while the mean-level stationarity may have been achieved, the changing variance could still affect model performance. In such cases, additional transformations like Box-Cox may be considered to stabilize the variance before modeling. (Appendix 5) .

Interpretation: Based on this result, we concluded that the appropriate order of differencing is I (d)=1 for the ARIMA model because the series became stationary after one differencing.
The same steps will be applied to ensure that the general exports time series is stationary.

3.7.3. Box-Cox Transformation

The Box-Cox transformation is a method used in time series analysis to stabilize the variance of a series, particularly when it is heteroskedasticity (i.e. the variance varies over time). This makes the series more consistent with the assumptions of statistical models such as ARIMA or SARIMA. This transformation depends on a parameter λ(lambda), which determines the nature of the transformation applied to the data. With Offshore Export Time Series In practice, as shown below, we obtain λ= 0.03, which is close to 0. This suggests that a logarithmic transformation is appropriate. To determine the value of λ, we used the Box Cox. lambda () function in R: (Appendix 4).

By using ggplot2, we obtained the Box-Cox transformed series. We can observe that the original values, which were in the range of hundreds and thousands, were compressed into smaller values, approximately between 1 and 9. This is expected behavior cause mathematically, since our Box-Cox lambda is close to 0, the transformation behaves like a logarithm. This compresses large values into a smaller range, explaining why the trans- formed series now falls approximately between 1 and 9. This compression stabilizes the variance over time and helps to meet the assumptions of the ARIMA/SARIMA models, making the series more suitable for accurate forecasting.

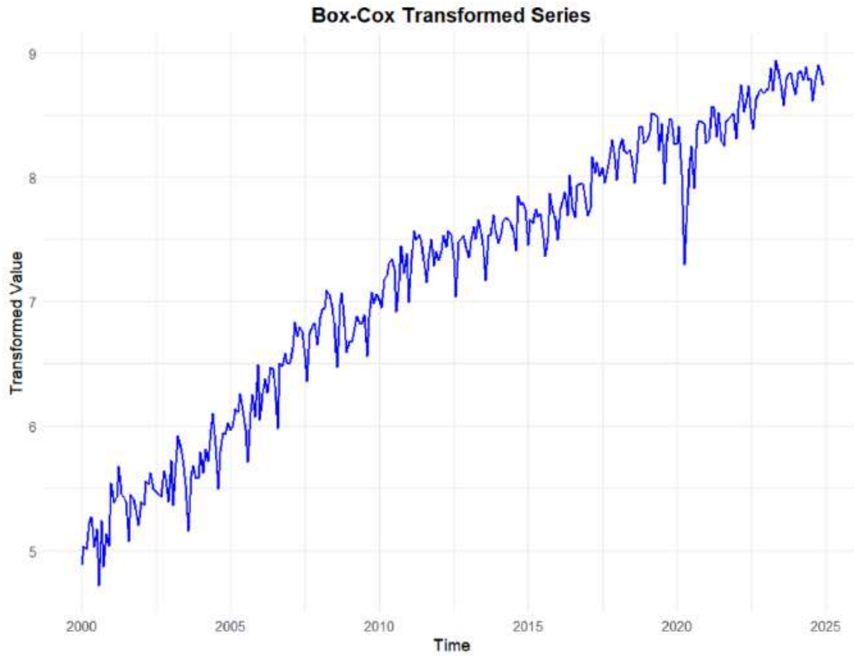

Figure 12.
BoxCox transformed series.

3.8. With General Export Time Series

In practice, by following the same steps as previously applied, we obtain $\lambda = 0.1$, which is close to 0. This suggests that a logarithmic transformation is appropriate. To determine the value of λ, we used the Box-Cox.lambda() function in R and obtained the following graph.

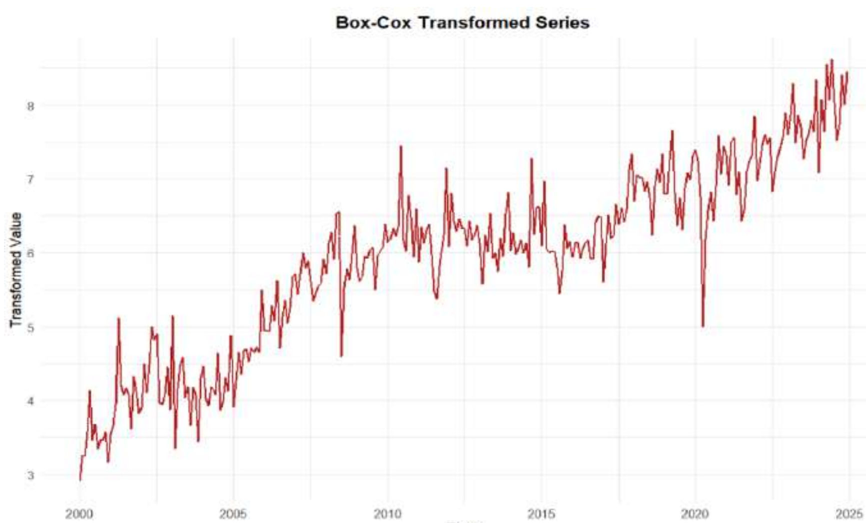

Figure 13.
BoxCox transformed series.

4. Modeling Process

4.1. Seasonality (Visualization, ACF/PACF)

After applying the Box-Cox transformation to stabilize the variance of the series, we performed a two-step differencing process to eliminate both trend and sea- sonal components. First, a simple difference was applied to remove the overall trend series using the diff (serie-boxcox, differences = 1) function, followed by a seasonal differencing with a lag of 12 to remove yearly seasonal patterns using diff (serie-diff, lag = 12) function. Once these transformations were complete, we analyzed the series to ensure that no residual seasonality remained.

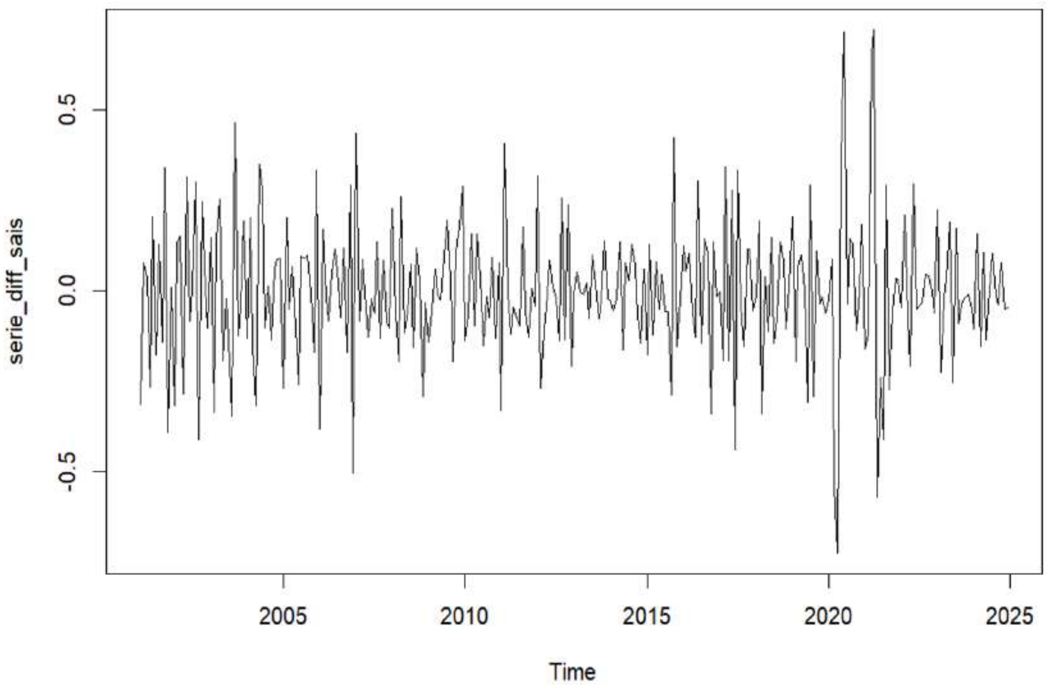

Figure 14.
Seasonality (Visualization, ACF/PACF).

This verification begins with a visual inspection of the differenced series, where we can see that the data become more stable over time,etc. followed by a more formal statistical analysis using the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF).

4.2. ACF Definition

ACF shows how much the values in a time series are related to their past values. It tells you: "Does today's value look like last month? Or two months ago?" If the ACF is high at lag 12, it means that the same pattern could be repeated every 12 months (seasonality).

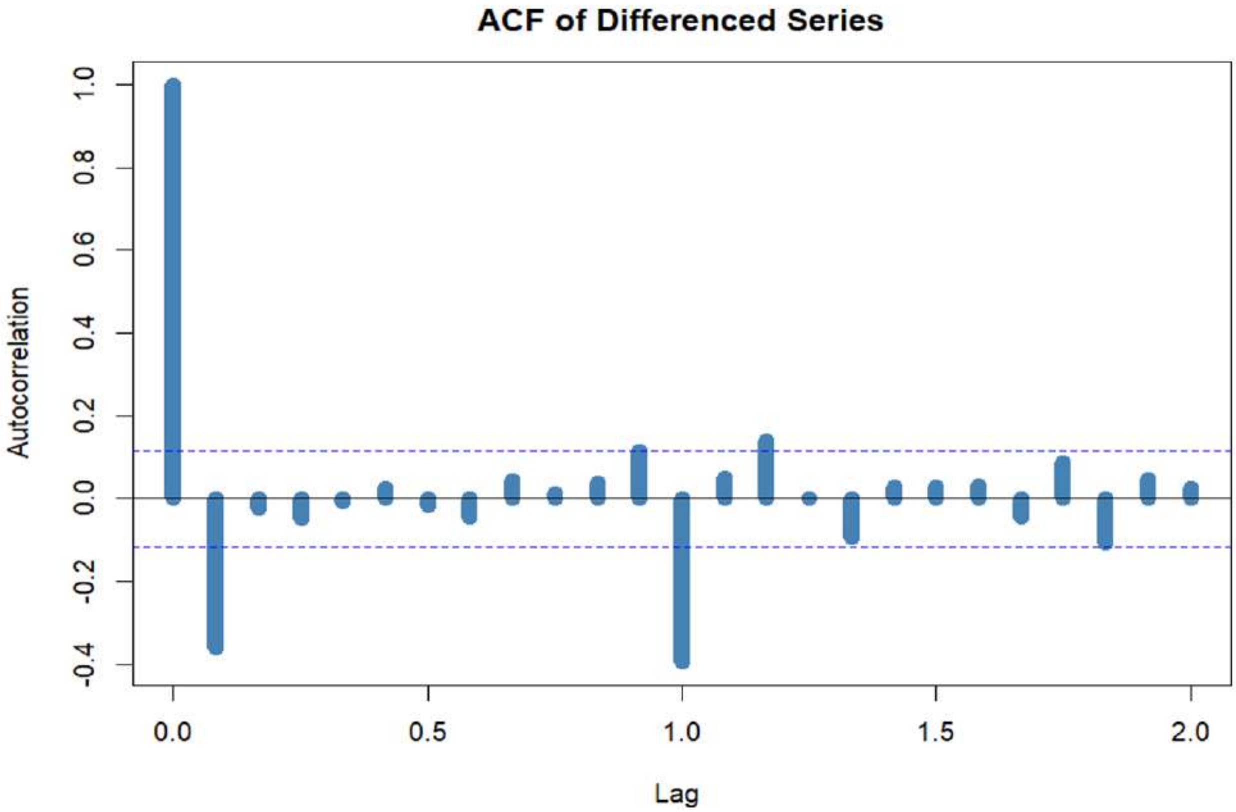

Figure 15.
ACF of Differenced series.

4.3. PACF Definition

PACF shows the direct relationship between a value and its past, removing the influence of the values in between. It tells you:"Is today's value directly influenced by the value 12 months ago, even if we ignore the values in between?"

```
pacf(serie_diff_sais, main = "PACF of Differenced Series",
     xlab = "Lag ",
     ylab = "Partial Autocorrelation",
     col = "steelblue",
     lwd = 10   )
```

Figure 16.
R code for PACF.

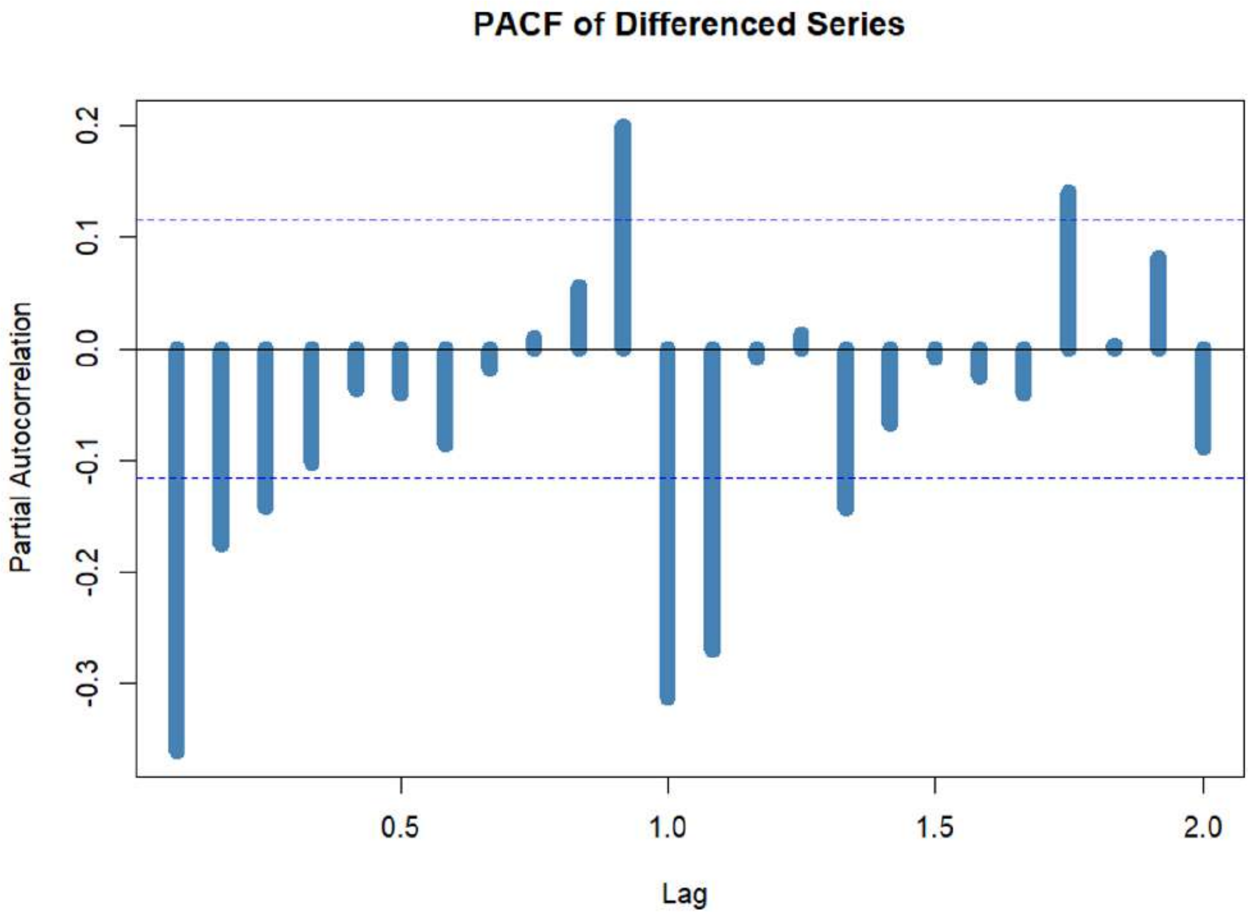

Figure 17.
PACF of Differenced series.

A significant spike at lag 0 is observed in both plots. However, this is expected and does not influence model selection, as it simply reflects the perfect correlation of the series with itself (i.e., autocorrelation at lag 0 is always 1 by definition). Therefore, to determine the appropriate orders:

- For AR (p): We examine the PACF plot starting from lag 1. The presence of a significant spike at lag 1 followed by a sharp drop suggests that an AR (1) component may be appropriate.
- For MA (q): We refer to the ACF plot, where significant autocorrelations at lag 1 followed by a rapid decline would support an MA (1) term.

Based on this analysis, the ARIMA (1,1,1) model was selected. This result refers to the offshore export data after applying all the necessary preprocessing and diagnostic steps. We will now proceed with the analysis of the general export series.

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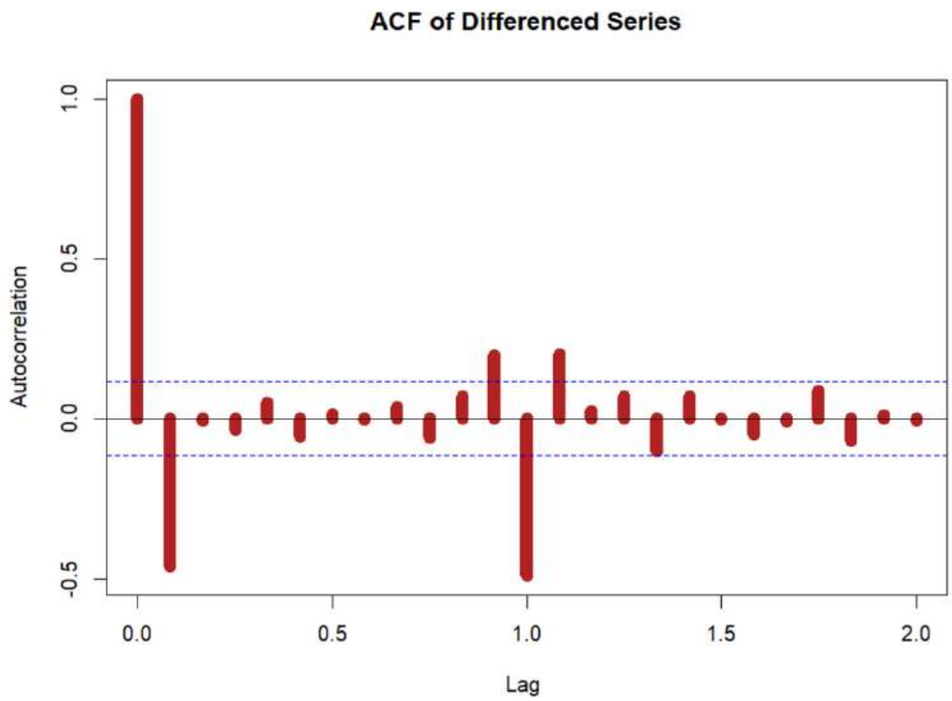

Figure 18.
ACF of Differenced series.

- For MA (q): We refer to the ACF plot, where significant autocorrelations at lag 1 followed by a rapid decline would support an MA (1) term.
-

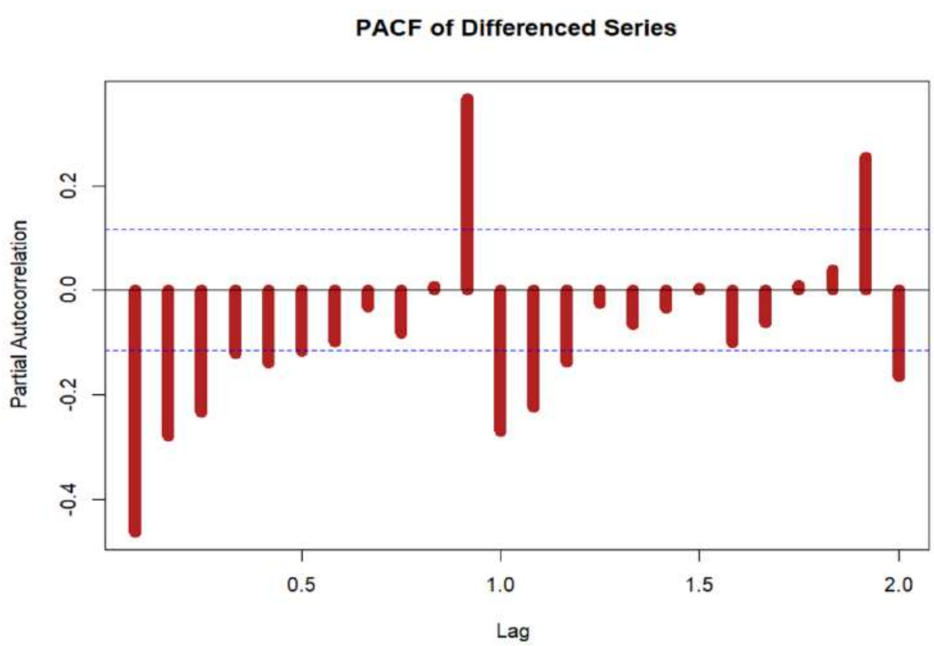

Figure 19.
PACF of Differenced series.

For AR (p): We examine the PACF plot starting from lag 1. The presence of a significant spike at lag 1 followed by a sharp drop suggests that an AR(1) component may be appropriate.

4.3.1. Residuals (ACF, Ljung-Box Test)

```
modele_sarima <- Arima(
  serie_ts,
  order = c(1, 1, 1),  # p, d, q
  seasonal = list(order = c(0, 1, 1), period = 12),

  lambda = boxcox_result
)
summary(modele_sarima)
checkresiduals(modele_sarima)
```

Figure 20.
R code.

The SARIMA model (modele_sarima) is fitted using the Arima() function, applied to the time series data serie_ts. The specified model includes non- seasonal parameters (p=1, d=1, q=1) and seasonal parameters (P=0, D=1, Q=1) with a seasonal period of 12, reflecting monthly seasonality. Additionally, a Box- Cox transformation (lambda = boxcox_result) is applied to stabilize the variance of the series and improve model accuracy. The summary(modele_sarima) function provides detailed model diagnostics, including coefficient estimates, statistical significance, and information criteria (such as AIC), which help assess the model's fit. Finally, checkresiduals(modele_sarima) is used to evaluate the quality of the residuals through plots and statistical tests; it checks whether the residuals behave like white noise (i.e., no pattern remains), which is essential for confirming the model's validity and predictive reliability.(Appendix 5).

The SARIMA model fitted to the series follows the structure ARIMA(1,1,1)(0,1,1)[8], incorporating both non-seasonal and seasonal components, with a Box-Cox transformation applied (lambda = 0.048) to stabilize the variance. The model shows good performance based on information criteria (AIC = -217.26, BIC.
= -202.62) and error metrics such as RMSE = 107.50 and MAPE = 8.31%, indicating reasonably accurate forecasts. The checkresiduals() function con- firms that the residuals behave like white noise: the Ljung-Box test yields a p-value of 0.4189, which is greater than 0.05. This means there is no significant autocorrelation left in the residuals, suggesting that the model fits the data well and the assumptions of the SARIMA model are satisfied.

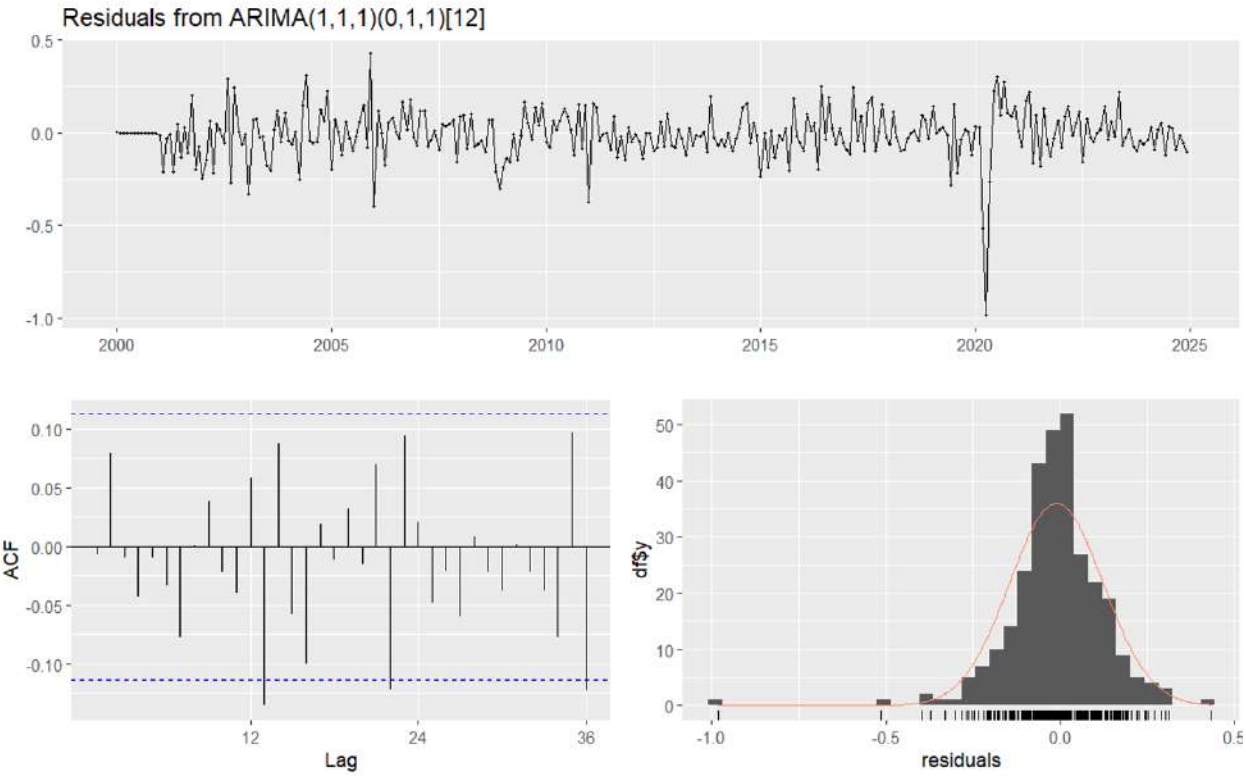

Figure 21.
Diagnostic Analysis of Residuals for the SARIMA (1,1,1)(0,1,1) Model: Assessing Model Adequacy.

This diagnostic plot helps evaluate whether the residuals (errors) of the SARIMA (1,1,1)(0,1,1) [8] model behave like random noise, which is necessary for a good forecast model.

- Top Plot – Residuals over time: This shows how the model's errors vary across time. The residuals seem to fluctuate around zero without a clear trend or repeating pattern, which is a good sign. It means the model captures most of the structure in the data. One large spike appears around 2020, likely due to an exceptional event, but overall, the errors stay relatively small.
- Bottom Left – ACF (Autocorrelation Function): This plot checks if the residuals are correlated over time. Almost all bars are within the dashed blue lines (confidence bounds), meaning there's no significant autocorrelation left in the residuals. That suggests the model has successfully captured the time-based patterns in the data.
- Bottom Right – Histogram of Residuals: This shows the distribution of the residuals. It appears roughly bell-shaped (normal distribution), with most values close to zero. This is what we expect in a well-fitted model, indicating the errors are normally distributed.

In short: The model fits the data well, and the errors look like random noise. So, it is safe to use this model to make predictions.

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4.3.2. Model Evaluation
4.3.2.1. AIC/BIC Comparison

```
# Create several models by testing different combinations of p, q, P, Q
model_111_011 <- Arima(serie_ts, order = c(1,1,1), seasonal = list(order = c(0,1,1), period = 12), lambda = boxcox_result)
model_211_011 <- Arima(serie_ts, order = c(2,1,1), seasonal = list(order = c(0,1,1), period = 12), lambda = boxcox_result)
model_111_111 <- Arima(serie_ts, order = c(1,1,1), seasonal = list(order = c(1,1,1), period = 12), lambda = boxcox_result)
model_211_111 <- Arima(serie_ts, order = c(2,1,1), seasonal = list(order = c(1,1,1), period = 12), lambda = boxcox_result)

models <- list(model_111_011, model_211_011, model_111_111, model_211_111)
names <- c("ARIMA(1,1,1)(0,1,1)", "ARIMA(2,1,1)(0,1,1)", "ARIMA(1,1,1)(1,1,1)", "ARIMA(2,1,1)(1,1,1)")

aic_values <- sapply(models, AIC)
bic_values <- sapply(models, BIC)

comparison <- data.frame(Model = names, AIC = aic_values, BIC = bic_values)
print(comparison)
```

Figure 22.
Estimation and Comparison of Seasonal ARIMA Models employing AIC and BIC (Generated by Author , 2025).

Interpretation: To identify the most suitable seasonal ARIMA model for the transformed time series (serie_ts), several candidate models were estimated using different combi- nations of non-seasonal and seasonal parameters. Specifically, four models were fitted: ARIMA(1,1,1)(0,1,1) [8], ARIMA(2,1,1)(0,1,1) [8], ARIMA(1,1,1)(1,1,1) [8], and ARIMA(2,1,1)(1,1,1) [8], where the Box-Cox transformation was applied to stabilize variance. The selection process was guided by information criteria, namely the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC), both of which balance model fit and complexity. The AIC and BIC values for each model were computed and summarized in a comparison table, allowing for an objective evaluation of performance. The model with the lowest AIC and BIC was considered the most appropriate for capturing the structure of the time series and for future forecasting.

Model	AIC	BIC
ARIMA(1,1,1)(0,1,1)	-217.2556	-202.6177
ARIMA(2,1,1)(0,1,1)	-219.5477	-201.2503
ARIMA(1,1,1)(1,1,1)	-215.7560	-197.4586
ARIMA(2,1,1)(1,1,1)	-218.1874	-196.2306

Figure 23.
Model Selection Based on Information Criteria.

Interpretation: Among the four candidate models, ARIMA (2,1,1)(0,1,1) [8] achieved the lowest AIC and BIC values, indicating the best overall performance in terms of fit and model simplicity. It is therefore selected as the most appropriate model for forecasting the given time series.

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4.4. Forecasting with ARIMA
4.4.1. Offshore Export Time Serie

```
forecast_values <- forecast(modele_sarima, h=12)

print(forecast_values)

predicted <- forecast_values$mean
print(predicted)

plot(forecast_values)
```

Figure 24.
Forecasting Offshore Export Time Series for 2025: ARIMA Model Predictions with Confidence Bands.

Interpretation: The R code used applies the forecast() function to the SARIMA model (modele_sarima) to generate a 12-month forecast (h=12) for the year 2025. This forecast includes the predicted values (point forecasts) as well as the confidence intervals 80% and 95%, which represent the range within which the actual values are likely to fall with a certain probability. The print(forecast_values) command displays the complete forecast object, showing both the predictions and their associated uncertainty. To extract only the expected values without the intervals, the code uses forecast_values$mean and stores the result in the predicted object, which is then printed to display a clean list of future values. Finally, the plot(forecast_values) function generates a visual representation of the forecast, including the historical data, the predicted future values, and the confidence intervals represented by shaded areas. This process allows for a clear and detailed analysis of future export trends while taking into account the uncertainty inherent in any prediction.

```
         Point Forecast    Lo 80    Hi 80    Lo 95    Hi 95
Jan 2025       2059.711 1786.169 2372.844 1655.735 2556.450
Feb 2025       2277.247 1949.585 2656.920 1794.824 2881.572
Mar 2025       2484.360 2112.583 2917.907 1937.861 3175.661
Apr 2025       2241.158 1892.205 2650.842 1729.076 2895.636
May 2025       2364.458 1985.314 2811.915 1808.795 3080.319
Jun 2025       2397.387 2001.682 2866.871 1818.220 3149.601
Jul 2025       2299.544 1908.635 2765.940 1728.192 3047.982
Aug 2025       1952.832 1609.674 2364.938 1452.086 2615.360
Sep 2025       2402.776 1973.977 2919.347 1777.546 3233.982
Oct 2025       2577.781 2108.385 3145.626 1894.065 3492.563
Nov 2025       2569.107 2090.797 3150.474 1873.217 3506.917
Dec 2025       2373.226 1920.468 2926.481 1715.380 3267.032
> predicted <- forecast_values$mean
> print(predicted)
          Jan      Feb      Mar      Apr      May      Jun      Jul      Aug      Sep      Oct      Nov      Dec
2025 2059.711 2277.247 2484.360 2241.158 2364.458 2397.387 2299.544 1952.832 2402.776 2577.781 2569.107 2373.226
```

Figure 25.
Monthly SARIMA Forecasts 2025: Estimates & Uncertainty.

Interpretation: For each month, the model provides:

- A mean forecast value (called the point forecast), which represents the model's best estimate,
- Two confidence intervals (at 80% and 95%), which reflect the uncertainty around the forecast.
- For example, in January 2025, the model forecasts approximately 2059.71 million dinars in exports. It estimates that:
- There is an 80% chance the actual value will fall between 1786.17 and 2372.84 million

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dinars,
- And a 95% chance it will be between 1655.74 and 2556.45 million dinars.

These intervals indicate that while the model provides a clear forecast, there is always some degree of uncertainty — the wider the interval, the more cautious the prediction. Overall, the forecasts suggest a positive trend in exports during certain months, particularly in October and November 2025, where the predicted values exceed 2500 million dinars. However, the relatively wide confidence intervals during these periods may indicate increased volatility or uncertainty in the export performance.

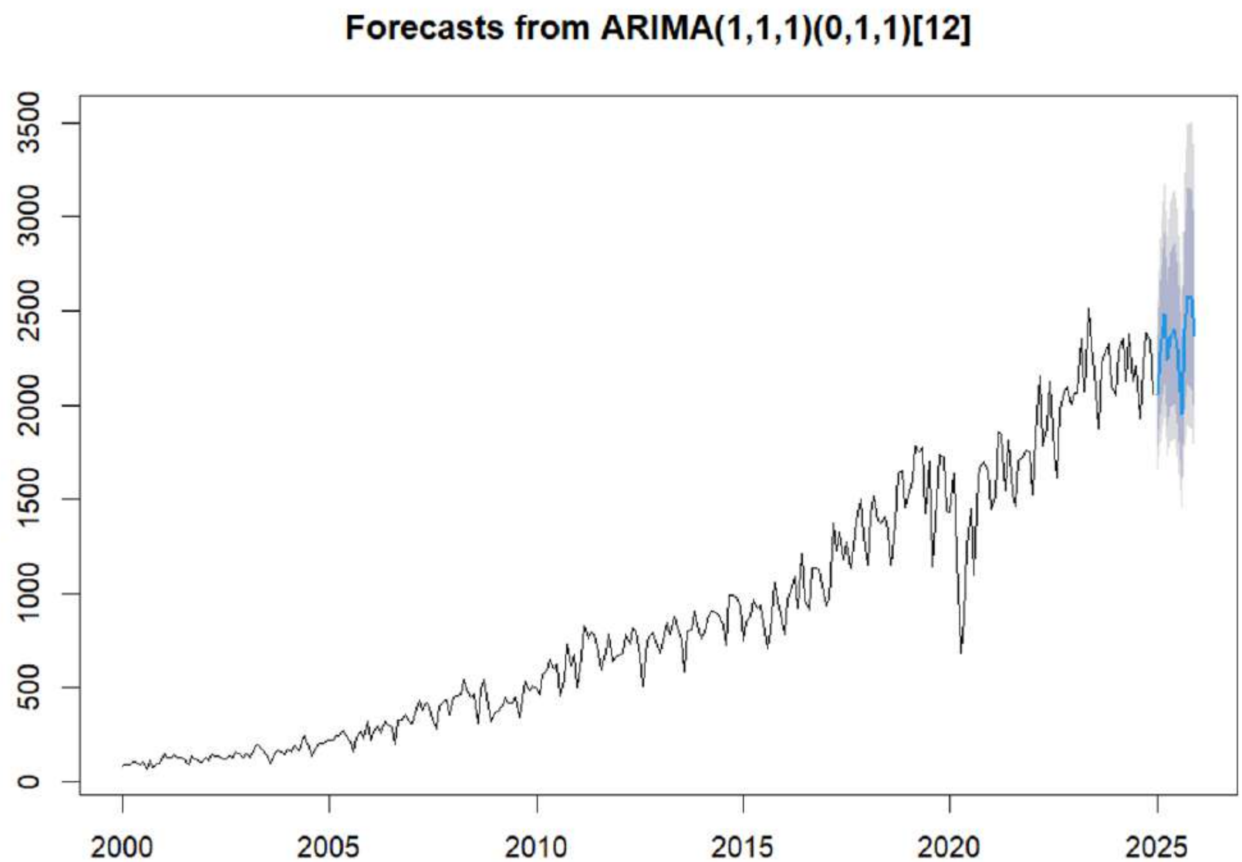

Figure 26.
Offshore Export Time Series Forecasting with ARIMA Models(Generated by Author , 2025)

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4.4.2. General Export Time Series

```
> forecast_values1 <- forecast(modele_sarima1, h=12)
> print(forecast_values1)
         Point Forecast    Lo 80    Hi 80    Lo 95    Hi 95
Jan 2025       182.0620 141.8002 233.0633 124.0755 265.3018
Feb 2025       206.5105 159.8017 266.0406 139.3383 303.8394
Mar 2025       211.9028 162.8237 274.8689 141.4349 315.0443
Apr 2025       204.0416 155.5875 266.6545 134.5917 306.8159
May 2025       200.5772 151.8450 263.9779 130.8427 304.8473
Jun 2025       212.0246 159.5405 280.6964 137.0239 325.1485
Jul 2025       181.6938 135.5147 242.6187 115.8341 282.2962
Aug 2025       169.9127 125.7769 228.5548 107.0731 266.9433
Sep 2025       198.3525 146.2212 267.8880 124.1979 313.5370
Oct 2025       223.6377 164.1266 303.3494 139.0699 355.8388
Nov 2025       215.4805 157.0878 294.1850 132.6251 346.2482
Dec 2025       258.7561 188.0401 354.3536 158.4852 417.7282
> predicted1 <- forecast_values1$mean
> print(predicted1)
          Jan      Feb      Mar      Apr      May      Jun      Jul      Aug      Sep      Oct      Nov      Dec
2025 182.0620 206.5105 211.9028 204.0416 200.5772 212.0246 181.6938 169.9127 198.3525 223.6377 215.4805 258.7561
```

Figure 27.
General Export Time Series Forecast: SARIMA Predictions with Confidence Intervals.

Interpretation: We applied the same forecasting steps to the time series of general exports to analyze and predict their future evolution. After preparing and modeling the data using the SARIMA approach, we generated a 12-month forecast. The table below presents the predicted export values along with confidence intervals, and the graph provides a visual representation of how exports are expected to change over the upcoming year. This forecast helps us better understand the possible trends and seasonal patterns in general exports, and can support strategic decision-making based on the predicted future behavior of the series.

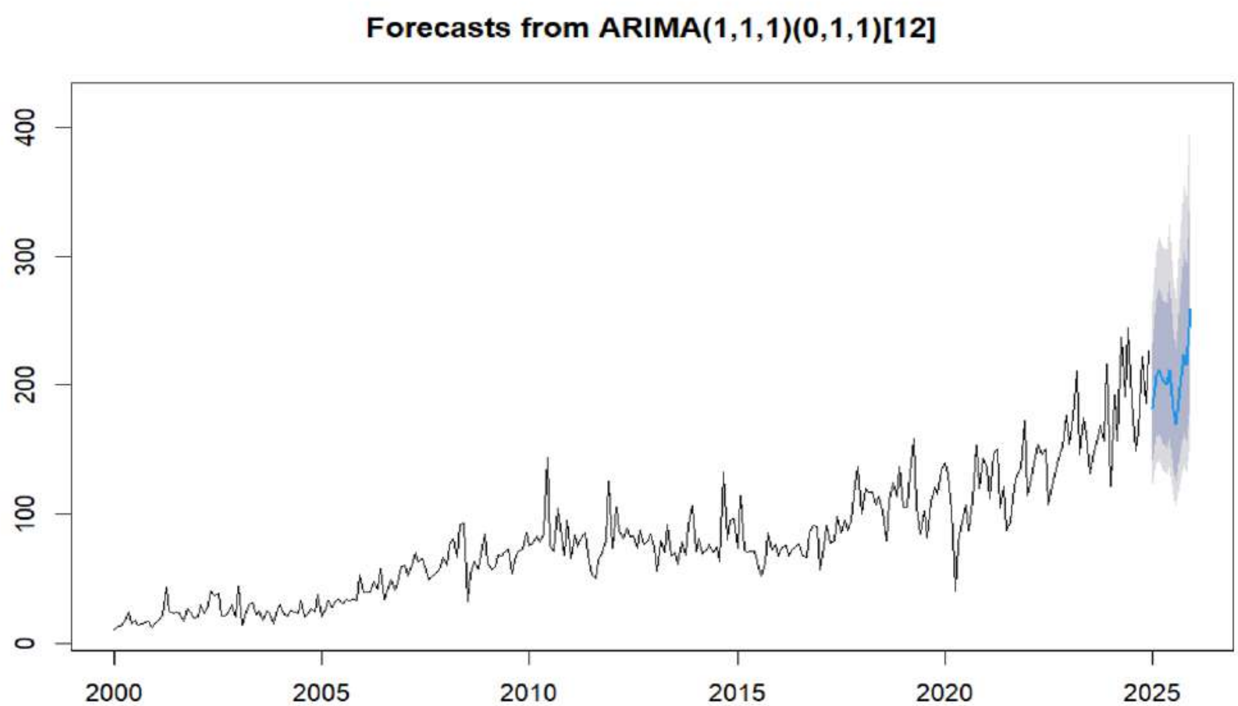

Figure 28.
General Export Time Series Forecasting with ARIMA Models.

4.5. Data Preparation and Visualization

4.5.1. Data Loading & Formatting

The export data was imported into Python using the pandas library. The Excel file was read and the 'Date' column was converted to a datetime format, which is crucial for accurate time series analysis. Setting the date as the DataFrame index enabled time-based operations and visualization.

4.5.1.1. Time Series Structuring

The 'Export_General' column, representing general export values, was isolated for analysis. Visualizations using matplotlib revealed the overall trend and fluctuations, providing initial insights before applying forecasting models.

4.5.1.2. Holt-Winters Exponential Smoothing Model

4.5.1.2.1. Model Application

The Holt-Winters model (using the statsmodels library) was applied to the 'Export_General' series, specifying both trend and seasonality as multiplicative—appropriate for data where seasonal effects grow over time. The model assumed a 12-month seasonality (annual cycle).

4.5.1.3. Forecast Generation

After fitting the model, a 12-month forecast was produced. Visualization compared historical data (in blue) with the forecast (in red), allowing for an intuitive assessment of the model's predictive behavior.

4.5.1.4. Offshore Export Series

The same preparation and modeling steps were repeated for the offshore export series, enabling comparison between general and offshore export trends.

4.5.1.5. ARIMA vs. Holt-Winters: Model Comparison

4.5.1.5. 1. Evaluation Approach

Since actual 2025 data was unavailable, a rigorous comparison was conducted using 2024 data, where real values exist. This out-of-sample validation is essential for objectively assessing model performance.

5. Results

The ARIMA model outperformed Holt-Winters on all metrics:
MAE: ARIMA (28.28) vs. Holt-Winters (32.06)
RMSE: ARIMA (36.89) vs. Holt-Winters (38.94)

This demonstrates ARIMA's superior ability to capture the variance and dynamics of Tunisian export data, at least for the tested period.

5.1. Strategic Implications for International Performance

From Forecast to Action

- Forecasting as a Strategic Tool:
  Accurate forecasts empower decision-makers to proactively strengthen Tunisia's international trade position, especially in the electromechanical sector.
- Marketing Strategies
- Offshore vs. General Exports:
- Offshore exports significantly outpace general exports, highlighting the need for differentiated marketing strategies:
- Standardization

- Treats all markets as a single entity, suitable for offshore exports where clients (often industrial/institutional) have homogenous expectations.
- Benefits: Cost reduction, efficiency, and consistency.
- Adaptation
- Adjusts marketing variables (product, packaging, promotion) to fit local market needs, crucial for general exports with diverse customer bases.
- Benefits: Enhanced customer satisfaction, increased competitiveness, and market share.
- Glocalization
- Combines a standardized core product with localized features (e.g., language, packaging).
- Balances efficiency with local relevance.
- Role of Policymakers and Export Institutions
- Support Measures:
- Enhance transport and trade infrastructure to ease export logistics.
- Provide educational resources and market intelligence to exporters.
- Facilitate the selection and implementation of effective marketing strategies.
- These recommendations align with recent research, emphasizing that accurate forecasting, combined with responsive marketing, drives export success.
- 5. Conclusions and Future Directions
- Model Performance: Both SARIMA and Holt-Winters effectively captured seasonality and trends, but SARIMA proved more accurate for this dataset, confirming its robustness for complex seasonal patterns.
- Strategic Value: Reliable forecasts inform not only statistical analysis but also strategic marketing and economic planning, enabling firms to anticipate demand, optimize pricing, and tailor promotional campaigns.
- Holistic Approach: The study bridges technical forecasting, economic policy, and marketing strategy, offering a framework usable by both policymakers and private sector managers.
- Limitations:
- Assumes stable external conditions (may not account for geopolitical shocks or sudden policy changes).
- Limited to historical export values does not integrate variables like exchange rates, production capacity, or global competition.
- Future Research:
- Incorporate advanced machine learning models (e.g., LSTM, XGBoost).
- Include multi-variable inputs for richer modeling.
- Extend analysis to other sectors and assess the real-world impact of forecast-driven decisions.

Table 1.
Summary table.

Aspect	**Holt-Winters**	**SARIMA/ARIMA**	**Strategic Implications**
Seasonality	Captures annual cycles	Handles complex seasonal patterns	Enables proactive planning
Accuracy (2024)	MAE: 32.06, RMSE: 38.94	MAE: 28.28, RMSE: 36.89	ARIMA recommended for forecasting
Marketing	Useful for broad trends	More precise for tactical decisions	Supports differentiated strategies
Policy	Baseline insights	Data-driven resource allocation	Informs export policy

5.2. Final Takeaway

This research highlights how advanced time series forecasting, when integrated with strategic marketing and policy support, can significantly enhance Tunisia's export competitiveness in the electromechanical sector. The findings advocate for a data-driven, differentiated approach to international marketing and underscore the importance of continuous model improvement and policy adaptation in a dynamic global environment.

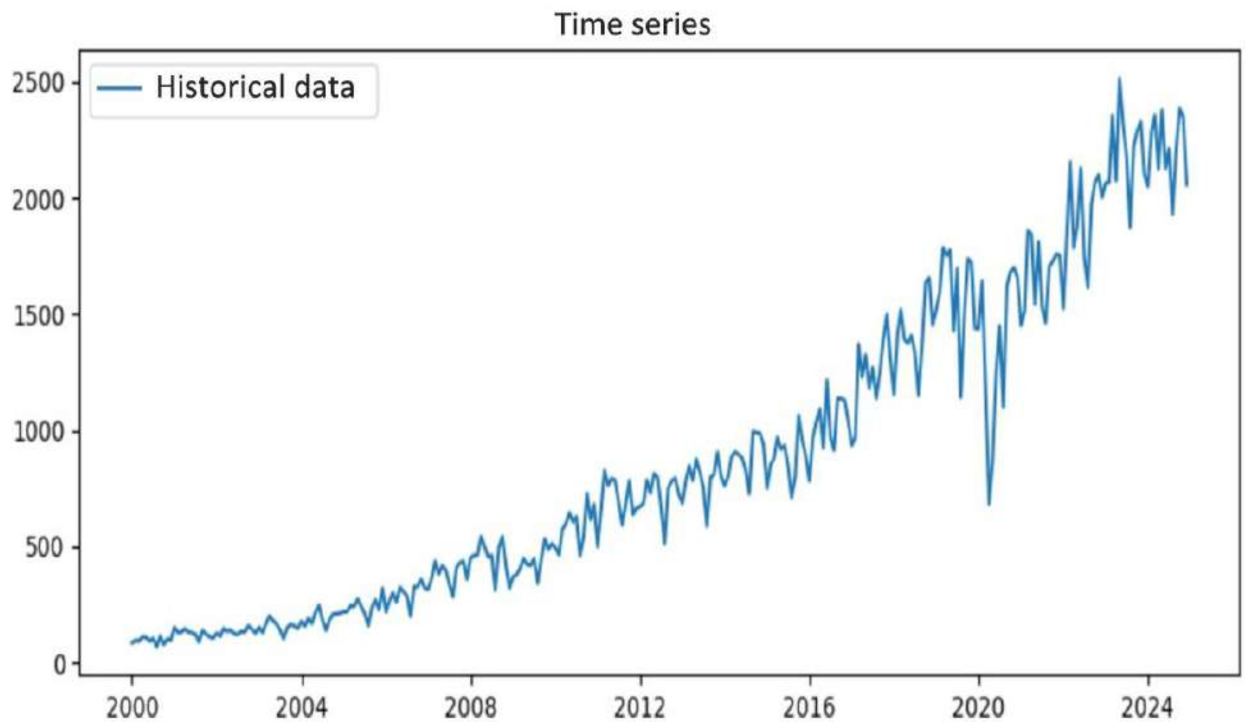

Figure 29.
Forecasting General Export Trends with Holt-Winters Exponential Smoothing (Multiplicative Seasonality, 2025).

6. Conclusion

This article has explored the forecasting of Tunisian mechanical and electrical exports for 2025 using advanced time series models specifically, SARIMA and Holt-Winters. Anchored in a comprehensive literature review and guided by a clear problem statement, the research addressed the dual objective of evaluating forecasting performance and translating results into actionable international marketing strategies.

From a data science perspective, both SARIMA and Holt-Winters models proved valuable in capturing seasonality and trends in export data. However, empirical results confirmed Hypothesis H1, demonstrating that SARIMA out- performed Holt-Winters in terms of forecast accuracy. This is consistent with previous studies Nguyen and Pham [1] and Hasibuan, et al. [2] that high- lighted SARIMA's robustness in handling complex seasonal patterns and long- term dependencies.

Beyond technical evaluation, the research validated Hypothesis H2, emphasizing that accurate forecasting provides firms with a strategic tool for optimizing international marketing efforts. Reliable export predictions allow companies to anticipate market demand, adjust pricing strategies, and plan promotional campaigns tailored to target regions. This aligns with the managerial implications highlighted in works like Ščeulovs and Gaile-Sarkane [7] and Kamsyakhan, et al. [4] who underline forecasting as a cornerstone of effective export management.

The integration of economic and managerial interpretations is a key contribution of this article. Forecasting is not presented as a purely statistical exercise but as a strategic decision-support system that connects macroeconomic planning to firm-level actions. The results suggest that the use of data science tools like SARIMA can inform export policy, improve resource allocation, and strengthen Tunisia's international trade position—particularly in high-potential sectors like electromechanical industries.

The value added by this article lies in its holistic approach bridging technical forecasting, economic planning, and marketing strategy. Compared to previous studies, it offers an integrated framework adaptable by both policymakers and private sector managers.

However, the study faces certain limitations. The models assume relative stability in external conditions, which may not fully capture geopolitical shocks or abrupt policy changes. Additionally, the dataset was limited to historical export values without incorporating variables such as exchange rates, production capacity, or international competition.

Looking ahead, future research could enhance the models by incorporating machine learning approaches (e.g., LSTM, XGBoost), integrating multi-variable inputs, or extending the analysis to other export sectors. Furthermore, studies could assess the impact of forecast-driven decisions on actual trade performance, thus closing the loop between prediction and implementation.

In conclusion, this article illustrates how data science and marketing can jointly contribute to national economic strategy, offering both theoretical insights and practical tools for boosting Tunisia's export competitiveness.

These findings are corroborated by more current studies in the literature highlighting the strategic importance of relational dynamics in banking [9] the effects of capital and liquidity on financial stability [10] and the evolving financial development-volatility nexus [11]. Further, advanced analytical techniques—i.e., machine learning (ML) for credit risk [12], ARDL modeling for sustainability of oil-exporting economies and AI-based LIBOR transition assessments [13]—are demonstrated to depict the modes through which data science continues to remake decision-making in marketing and finance.

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

Copyright:

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```r
# Create the time series
serie <- ts(data$`exportation ( off shore)`, start = c(2000, 1), frequency = 12)

# Plot the original time series
plot(serie, main = "serie originale avec outliers")

# Apply automatic outlier detection
res <- tso(serie, types = c("AO", "LS", "TC"))

# Extract the adjusted (outlier-corrected) series
serie_corrigee <- res$yadj

# Convert to a data frame for visualization
df <- data.frame(
  Date = as.yearmon(time(serie)),
  Original = as.numeric(serie),
  Corrected = as.numeric(serie_corrigee)
)

# Plot both the original and corrected series
ggplot(df, aes(x = Date)) +
  geom_line(aes(y = Original, color = "Original")) +
  geom_line(aes(y = Corrected, color = "Corrected")) +
  labs(title = "Comparison of Original vs Corrected Series",
       color = "Series") +
  theme_minimal()

# Display the outlier detection results
print(res)
plot(res)
```

Appendix 1.
Code – Indicator Modeling.

```
Series: serie
Regression with ARIMA(0,1,1)(1,0,0)[12] errors

Coefficients:
          ma1    sar1     TC231      LS234      TC244     TC255     LS266     TC281
      -0.7636  0.6679  334.7500  -194.6643  -756.8586  348.2670  274.3463  311.1931
s.e.   0.0383  0.0429   62.2683    49.6731    62.6579   64.6375   50.4721   58.8505

sigma^2 = 7453:  log likelihood = -1757.15
AIC=3532.31   AICc=3532.93   BIC=3565.61

Outliers:
  type ind    time coefhat   tstat
1   TC 231 2019:03   334.8   5.376
2   LS 234 2019:06  -194.7  -3.919
3   TC 244 2020:04  -756.9 -12.079
4   TC 255 2021:03   348.3   5.388
5   LS 266 2022:02   274.3   5.436
6   TC 281 2023:05   311.2   5.288
```

Appendix 2.
Results Overview.

```
> checkresiduals(fit_corrected)

        Ljung-Box test

data:  Residuals from ARIMA(0,1,2)(1,0,0)[12] with drift
Q* = 37.24, df = 21, p-value = 0.0158

Model df: 3.   Total lags used: 24

> Box.test(residuals(fit_corrected), type = "Ljung-Box")

        Box-Ljung test

data:  residuals(fit_corrected)
X-squared = 0.010366, df = 1, p-value = 0.9189

> AIC(fit_corrected)
[1] 3517.498
> AIC(fit_sarima)
[1] 3701.612
```

Appendix 3.
Results of the validation.

```
serie1 <- ts(data$`exportation ( off shore)`, start = c(2000, 1), frequency = 12)

# Simple differentiation
diff_serie1 <- diff(serie1, differences = 1)
dates <- time(diff_simple)

# Display of differentiated series
plot(diff_simple, type = "l", col = "blue", lwd = 2,
     main = "Differentiated series (Simple differentiation method)",
     xlab = "Time", ylab = "Differences between periods")
```

Appendix 4.
Time series differentiation.

```r
library(tseries)

#Apply the ADF test to your series
result <- adf.test(diff_serie)

# Capture the output and print it together
capture.output({
  print(result)
  if (result$p.value<0.05)
  {cat("conclusion : The series is stationary")
  }else{ cat("conclusion : The series isn't stationary")}})
```

```
"\tAugmented Dickey-Fuller Test"
""
"data:  diff_serie"
"Dickey-Fuller = -16.514, Lag order = 2, p-value = 0.01"
"alternative hypothesis: stationary"
""
"conclusion : The series is stationary"
```

Appendix 5.
Dickey-Fuller Test.

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