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Forecasting Air Cargo Demand of Saudia Cargo Company

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Abstract**—***Air cargo has played a crucial role in getting time-sensitive and high-value shipments from one point to another as quickly as possible internationally and domestically. It is a trade facilitator that contributes to global economic development and creates millions of jobs. The worldwide economy relies on the capacity to provide high-caliber products at competitive prices to consumers around the globe. The air cargo sector plays a pivotal role in achieving Saudi Arabia objectives aimed at turning the Kingdom into a global logistics hub for goods transport and cargo services. Forecasting is an important factor to any business because it gives the ability to make informed business decisions and establish data-driven strategies. The objective of this study is to implement various forecasting methods of time series decomposition, ARIMA models, LSTM neural networks, and ANN neural networks to forecast and estimate monthly demand of air cargo business in terms of weight for year 2024 and beyond. Results indicate that ARIMA models excelled in AME, EUR, AFR, and KSA regions, capturing stable seasonal trends, while LSTM neural networks performed best in MNT and ISC regions, and decomposition was most effective for FES region. ANN models did not outperform others in any region. The study recommends using region-specific models, prioritizing ARIMA for its reliability, and integrating external factors to improve accuracy. Investing in tools and training ensures better forecasting precision.*

Keywords**—** *Air Cargo, Demand Forecasting, Time Series, ARIMA, Neural Network, Decomposition.*

I. INTRODUCTION

For over a century now, air cargo has played a crucial role in getting time-sensitive and high-value shipments from one point to another as quickly as possible internationally and domestically. Over time, air transportation has demonstrated its significance as a vital “link” between producers and customers. As stated by the International Air Transport Association (IATA), air freight has been essential in providing critical medical supplies (such as repair components and spare parts) and pharmaceuticals. Air transportation has enabled nations to engage in the worldwide market by granting them access to essential markets and fostering globalization. Air transport additionally supports countries in focusing on tasks where they hold a comparative advantage. It also aids in promoting trade with nations that offer different products and services.

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Saudia Cargo company is a leading cargo carrier based in Saudi Arabia with global reach. Through scheduled and charter services on freighters combined with the cargo capacity on Saudi Arabian Airlines passenger services and interline with airline partners it provides services to all major destinations ensuring reliability, safety, security, and convenient connections. As it is being at the heart of the world, the Gulf, via three hubs in Saudi Arabia; JEDDAH, RIYADH and DMMAM, giving it a unique competitive edge, increased flexibility and allowing it to move cargo with ease. The company plays a pivotal role in the air cargo sector in achieving the objectives of Vision 2030 aimed at turning the Kingdom into a global logistics hub for goods transport and cargo services. The Kingdom’s strategic and geographic location make it a major station for goods and a crossroad for international cargo routes. This location will help the Kingdom become a pivotal logistics and cargo platform; let alone it will provide good opportunities for the country to increase its share of logistics operations.

II. STATEMENT OF THE PROBLEM

Forecasting is an important factor to any business, enabling organizations to make informed decisions and develop data-driven strategies. It is vital for companies to be always planning in advance in order to ensure the readiness to take on future demands as well as challenges and this is no different for companies in the air cargo industry, particularly in this post pandemic crisis downturn.

This study was conducted due to higher importance of accurate forecasting and requirements of management in Saudia Cargo company to prepare budget for next year and monthly forecasting for next 12 month as the company intended to improve the budget process as this is one of the initiatives to be achieved during this year and also to reflect high fluctuation in air cargo demand in the world which was extremely affected by COVID-19 and reduction of capacity in most airlines; but today they are coming back to business with high frequencies of flights which might increase or decrease the demand. Current Russia-Ukraine war is currently affecting the whole business in air cargo and supply chain industry, and this is another reason to forecast demand monthly and prepare reasonable budget for the next year.

III. OBJECTIVE OF THE STUDY

This study is aimed at forecasting the monthly demand in terms of chargeable weight (kg) to be transported onboard freighter and passenger flights for the year 2024. Another key objective is to identify a suitable forecasting model that is both accurate and easy to implement using various software tools,

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such as Microsoft Excel. Additionally, the study seeks to develop an automated module that allows for adjustments to input parameters, enabling flexibility and adaptability in the forecasting process. By achieving these objectives, the study intends to generate reliable forecasts that account for seasonality, reflect the historical growth in tonnage, and align with the company's strategic initiatives to increase cargo volumes. The research will answer the following questions:

Q1) How accurately can cargo demand be predicted, and how closely do these predictions align with actual trends?

Q2) What is the most effective method for forecasting air cargo demand, ensuring precision?

Q3) What will be the forecasted monthly demand for year 2024, using the most reliable method with minimal forecasting errors?

IV. Literature Review

Econometric modeling evaluates economic factors like GDP, trade, and fuel prices to create forecasts linked to expectations of these variables (Griliches & Intriligator, 1983). Forecasting aids airlines in planning. Short-term forecasts guide operations, while long-term forecasts support strategic decisions. Deseasonalizing data improves forecast accuracy for demand fluctuations (Wickham, 1995). ARIMA models effectively address seasonality and trends in air cargo, demonstrating superior accuracy for short-term forecasts compared to other statistical methods (Chatfield, 1996). Accurate air cargo demand forecasting is crucial for supply chain alignment, with GDP and trade volumes significantly influencing planning and resource allocation (Wensveen, 1996). Late 1990s studies emphasized sophisticated models to incorporate seasonal patterns, like holidays and agriculture cycles, which significantly influence air cargo demand (Smith & Lambert, 1998). Globalization and trade liberalization drive sudden air cargo demand spikes, highlighting the importance of adaptive forecasting methods to manage rapid trade flow changes (Johnson, 2001). A study found no clear link between forecast accuracy and revenue performance in airline revenue management, challenging traditional assumptions based on error metrics (Usman, 2003). Customer expectations for speed and reliability have reshaped air cargo demand, urging providers to enhance service quality and adopt real-time tracking technologies (Brown et al., 2004). E-commerce growth in the 2000s transformed air cargo, boosting shipment volumes and necessitating digital forecasting tools for dynamic logistics (Lee, 2005). Mid-2000s econometric studies established GDP as a key driver of air cargo trends, forming a basis for long-term demand forecasting (Anderson & Hall, 2006). Air cargo demand forecasting is vital for analyzing schedules and facility needs. Global traffic is expected to grow 6.1% annually, driven by strategic optimizations (Boeing, 2007). Fuzzy regression models improve air cargo forecasting by incorporating uncertainty factors. GDP significantly influences air cargo volume, particularly for Taiwan's exports and imports (Choe et al., 2007; Chou et al., 2007). Refrigeration advancements and changing consumer preferences increased demand for perishable goods, prompting tailored forecasting strategies for high-value, time-sensitive commodities (Thompson, 2007). ARIMA models outperform others in predicting short-term cargo volumes, supporting time series analysis for accurate and actionable forecasting (Williams, 2008). The 2008 financial crisis highlighted the need for revised forecasting methods to address economic downturns and air cargo market volatility (Hughes, 2009). Early 2010s studies urged including sustainability metrics in forecasting to align air cargo operations with environmental goals and reduce carbon footprints (Green et al., 2010). Machine learning techniques enhance forecasting by processing large datasets and identifying complex air cargo demand patterns (Kim & Park, 2011). Air cargo demand grew 6.9% annually from 1996–2004, driven by high-tech manufacturing and e-commerce. GDP significantly influences demand, alongside trade and FDI (Suryani et al., 2012). Sri Lankan export-driven shipping demand is strongly linked to export performance. Regression and VAR models effectively forecast shipping needs based on export data (Nadeesha & Silva, 2013). Holt-Winters outperformed ARIMA in forecasting accuracy, reducing overbooking and offloading effects using chargeable weight time series (Klindokmai et al., 2014). Multiple forecasting techniques, including econometric modeling and trend analysis, address complex managerial problems, each suited to specific forecasting scenarios (Li, Zhou, Xie, & Wu, 2007). Medium and long-range forecasts are particularly effective for regional market planning and decision-making (Greene, 2003). Trend analysis evaluates economic changes, while potential analysis forecasts early-stage market developments, aiding in understanding marketplace dynamics (Pierce, 2004). Forecasting techniques must be carefully selected to balance their strengths and limitations for specific applications (Leung, Cheung, & Hai, 2000). Simulations utilizing the Potluck Problem model precisely forecast cargo demand, taking into account elements such as GDP, holidays, and load factors on particular routes (Totamane et al., 2014). Geopolitical events, such as conflicts and trade disputes, significantly impact cargo routing and demand, necessitating resilient forecasting systems (Khan, 2014). Time series analysis struggles with volatility, while regression identifies air cargo growth factors like GDP and fuel prices, though causation cannot be inferred (Transportation Research Board, 2015). Big data analytics enhances air cargo forecasting by processing diverse datasets, improving precision and demand management (Singh et al., 2015). Advanced computational methods in time series decomposition improve forecasts by addressing seasonal and cyclical variations (Makridakis et al., 2015). Blockchain technology enhances supply chain transparency and efficiency, potentially boosting demand through improved trust (Patel, 2017). Neural networks excel in forecasting by effectively handling non-linear relationships and large datasets, outperforming traditional models in complex scenarios (Friedman & Wang, 2018). Regional economic integration significantly impacts air cargo flows, requiring adaptive forecasting models for navigating integrated market complexities (Zhang & Li, 2018). Neural networks provide higher accuracy in air cargo forecasting by integrating historical and real-time data, effectively adapting to

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fluctuating demand patterns (Liu et al., 2019). Research comparing MLR, ARIMA, SVR, neural networks, and GBRT found SVR outperformed other models, with ARIMA also performing well for air cargo demand forecasting (Liu et al., 2020). The COVID-19 pandemic emphasized the need for flexible forecasting systems to address global disruptions in air cargo demand (Wang et al., 2020). Hybrid ARIMA models combining machine learning improve accuracy by addressing ARIMA's limitations in capturing complex patterns (Wang et al., 2021). Digital technologies like AI and IoT enhance operational efficiency and forecasting accuracy during disruptions like the COVID-19 pandemic (Garcia & Ahmed, 2021). Hybrid models combining traditional and machine learning methods improve forecast reliability and adaptability in volatile markets (Clark et al., 2022). Machine learning with time series decomposition enhances forecasting by isolating specific patterns for improved accuracy (Brown et al., 2022). Sustainable aviation fuels are key to future air cargo forecasting, aligning industry growth with environmental compliance and sustainability goals (Roberts, 2023). Advanced simulation tools enhance capacity management by modeling complex scenarios and aiding strategic decisions (Nelson et al., 2023). Deep learning models improve air cargo forecasting reliability by capturing seasonality and trends in complex datasets (Zhang et al., 2023).

V. METHODOLOGY

The methodologies employed in this thesis to achieve its objectives are outlined as follows: Airports and countries are categorized into seven global regions to streamline analysis and forecasting. These regions are defined as: Saudi Arabia (KSA), the American Region (AME), the European Region (EUR), the Middle East and North Africa Region (MNT), the African Region (AFR), the Indian Sub-Continent Region (ISC), and the Far East Region (FES). This classification ensures a structured approach to studying diverse geographical markets.

To build on this structure, historical monthly data of actual flown tonnages by Saudia Cargo Company over the past six years (2018-2023) was collected for each region. This dataset served as the foundational input for the analysis, capturing trends and seasonality inherent to each region's cargo demand.

Subsequently, multiple forecasting methods were applied to estimate future cargo demand for each region based on historical trends. The forecasted results were then compared with the actual tonnages recorded for 2023 to validate the accuracy and effectiveness of each method.

To evaluate the performance and reliability of the applied forecasting methods, accuracy measures such as Mean Absolute Percentage Error (MAPE), Mean Absolute Deviation (MAD), and Mean Squared Error (MSE) were employed. These metrics provide quantitative insights into the methods' precision and robustness.

Based on these evaluations, the most effective forecasting method was identified and applied to predict monthly cargo demand for 2024 and subsequent years. This step aimed to generate reliable forecasts that can support strategic decision-making for Saudia Cargo Company in planning and resource allocation.

VI. RESULTS

The data pattern of all regions seems to be nonstationary, or trend based on the analysis of autocorrelation coefficients which are significantly different from zero for the first three lags and then gradually drop to zero. Therefore, specific forecasting techniques that can be applied such as time series decomposition, ARIMA (BOX-JINKENS), LSTM neural network, and ANN neural network.

A. Time Series Decomposition Method

Time series decomposition is a statistical technique used to break down a time series into several distinct components: Trend (T), Seasonal (S), Cyclical (C), and Irregular (I). The primary goal of decomposition is to understand and analyze the individual elements that contribute to the observed variation in a time series over time. Each region was analyzed using time multiplicative decomposition technique in MINITAB software to derive the trend equation and seasonal indices, which are incorporated into the following equation to forecast the next month's values (Y_t):

$$Y_t = T_t \times S_t \times C_t \times I_t \qquad (1)$$

The results of applying multiplicative decomposition for each region are shown in table 1.

TABLE 1. Forecast accuracy metrics for applying time series decomposition.

Region	MAPE	MAD	MSD
AME	15%	157	40,777
EUR	12%	884	1,118,508
AFR	12%	290	144,493
MNT	27%	613	659,926
KSA	32%	380	263,003
ISC	33%	1,221	2,412,382
FES	14%	554	568,092

The accuracy of the forecasts, measured by MAPE, ranges from 12% to 32% across regions when applying multiplicative decomposition. This forecasting technique captured the distinct seasonal patterns and long-term trends unique to each region, enhancing the precision of the forecasts.

B. ARIMA (BOX-JINKENS) Method

ARIMA (Autoregressive Integrated Moving Average), or the Box-Jenkins approach, is a widely used forecasting method for univariate time series. It addresses autocorrelation and handles both stationary and non-stationary data through differencing, offering a versatile framework for analyzing and predicting trends, represented as ARIMA (p, d, q). The model's components of autoregressive (AR) terms, differencing (I), and moving average (MA) terms allow it to capture complex patterns in time series data effectively

By examining the sample autocorrelations for each region, they indicated that all series are nonstationary and does not vary about a fixed level. This is supported by the observation that the first several autocorrelations were consistently large and trailed off to zero. To create stationary series and eliminate the trend, the series were differenced with respect to the seasonal lag of period S =12.

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The sample autocorrelations (ACF) and sample partial autocorrelations (PACF) of the differenced series for each region were examined to identify suitable ARIMA models. Residual analysis was conducted to evaluate the adequacy of these models. Table 2 presents the forecast accuracy metrics, including Mean Absolute Percentage Error (MAPE), Mean Absolute Deviation (MAD), and Mean Squared Deviation (MSD), for the models selected in each region. These models were chosen based on their ability to produce accurate forecasts while ensuring the absence of significant residual autocorrelations.

TABLE 2. Forecast accuracy metrics for selected ARIMA models.

Region	Selected Model	MAPE	MAD	MSD
AME	ARIMA(1,0,1)(1,1,1)$_{12}$	12%	124	24,100
EUR	ARIMA(2,0,3)(1,1,1)$_{12}$	8%	620	596,844
AFR	ARIMA(1,0,1)(1,1,0)$_{12}$	10%	257	112,486
MNT	ARIMA(1,0,4)(1,1,1)$_{12}$	24%	494	423,590
KSA	ARIMA(1,0,3)(1,1,1)$_{12}$	30%	307	170,093
ISC	ARIMA(1,0,2)(1,1,1)$_{12}$	23%	780	1,254,616
FES	ARIMA(1,0,2)(0,1,0)$_{12}$	15%	640	731,868

The ARIMA method performed strongly, with MAPE ranging from 8% to 30%, demonstrating its effectiveness and reliability in forecasting air cargo demand across all regions.

C. LSTM Neural Networks for Forecasting

Neural networks, inspired by the human brain, are key machine learning models used for tasks like image recognition, natural language processing, and time series forecasting. They consist of interconnected layers of neurons that process and transform input data. Neural networks are widely used in time series forecasting because of their ability to model complex, nonlinear relationships and capture temporal dependencies within data. Types of neural network include Feedforward Neural Networks (FNNs) for simple tasks, Convolutional Neural Networks (CNNs) for image data, Recurrent Neural Networks (RNNs) for sequential data, and Transformers for advanced NLP tasks. For time series forecasting, recurrent neural networks (RNNs) are particularly relevant. These networks are designed to handle sequential data by maintaining a memory of previous inputs.

The Long Short-Term Memory (LSTM) Neural Network is a specialized type of Recurrent Neural Network (RNN) designed for sequential data and time-series tasks. It addresses challenges like the vanishing gradient problem through memory cells and gating mechanisms, enabling it to learn and retain both short-term and long-term patterns. These features make LSTMs ideal for forecasting, as they can effectively capture temporal dependencies and trends in data, such as seasonality, recurring patterns, and irregular fluctuations.

The implementation of an LSTM neural network for sales forecasting using MATLAB R2024b involves five key steps: (1) Data Preparation, where historical sales data is split into training (70%), validation (15%), and testing (15%) subsets and normalized; (2) LSTM Network Design, defining the architecture with input, LSTM, fully connected, and regression layers, and experimenting with different layer and neuron configurations; (3) Training the Network, specifying training options such as the Adam optimizer and monitoring training and validation loss to avoid overfitting; (4) Testing and Evaluation, using the trained model to forecast the test set, compute error metrics (MAPE, MAD, MSD), and assess model performance; and (5) Forecasting and Visualization, generating future predictions, reversing normalization for interpretation, and visualizing actual, test set, and forecasted data for the next period.

Several experiments were conducted with varying network architectures, testing 1, 2, and 3 LSTM layers and different neuron counts (100, 150, and 200) to identify the best-performing network. Table 3 presents the MAPE results for all nine network models across each region. The AFR and KSA regions exhibit the highest MAPE values, exceeding 100%, which is significantly higher compared to other regions.

TABLE 3. MAPE results for tested models of LSTM Neural Network.

Layers	**1 Layer**			**2 Layers**			**3 Layers**		
Neuron	**100**	**150**	**200**	**100**	**150**	**200**	**100**	**150**	**200**
NW	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
AME	22%	19%	27%	60%	48%	22%	22%	71%	45%
EUR	31%	24%	19%	21%	26%	23%	24%	29%	29%
AFR	111 %	105 %	97%	105 %	107 %	108 %	103 %	104 %	110 %
MNT	61%	36%	56%	47%	17%	25%	53%	37%	27%
KSA	127 %	111 %	100 %	104 %	107 %	117 %	77%	94%	80%
ISC	21%	37%	31%	10%	29%	24%	31%	32%	23%
FES	22%	27%	30%	25%	21%	30%	15%	35%	23%

The model with the best performance for each region was selected based on accuracy measurements, as shown in Table 4, along with the corresponding MAPE, MAD, and MSD results.

TABLE 4. Forecast accuracy metrics for selected models of LSTM Neural Network.

Region	Selected Model	MAPE	MAD	MSD
AME	1 Layer, 150 Neurons	18.6%	177	37,729
EUR	1 Layer, 200 Neurons	19.3%	1,204	2,072,124
AFR	1 Layer, 200 Neurons	96.8%	1,411	2,850,584
MNT	2 Layers, 150 Neurons	17.5%	499	332,640
KSA	3 Layers, 100 Neurons	77.3%	785	663,739
ISC	2 Layers, 100 Neurons	9.6%	526	366,985
FES	3 Layers, 100 Neurons	15.4%	1,173	1,717,886

There is no single type of LSTM neural network that consistently outperformed others across all regions among the selected models. Performance varied depending on the region, with each model demonstrating strengths tailored to specific data characteristics. Notably, the ISC region achieved a MAPE of 9.6%, which is exceptionally low, and indicative of strong forecasting accuracy compared to models for other regions.

D. ANN Neural Networks for Forecasting

Artificial Neural Networks (ANNs) are simple feedforward networks (FNNs) commonly used for time-series forecasting by mapping historical data to future predictions. They process inputs independently without retaining sequence memory, requiring preprocessing techniques like lagged features to handle temporal dependencies.

ANNs and LSTM neural networks differ significantly in their capabilities and applications. While ANNs use a simple feedforward structure, LSTMs feature a recurrent design with memory cells, enabling them to model long-term

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dependencies and capture complex patterns like trends and seasonality. ANNs rely on extensive preprocessing for sequential data, while LSTMs automatically process temporal relationships. However, ANNs are faster and easier to train, making them suitable for simpler tasks, whereas LSTMs are better for complex, long-term forecasting due to their advanced memory mechanisms and ability to handle missing data more effectively.

Forecasting demand of each region with ANN in Visual Gene Developer involves five steps: (1) Data Preparation, splitting historical sales data into training and validation sets and normalizing it; (2) ANN Network Design, defining input, hidden, and output layers, and experimenting with different configurations to optimize performance; (3) Training the Network, using settings like a small learning rate, momentum coefficient, and target error for precise predictions; (4) Recall and Validate, using the trained model to forecast validation data; and (5) Forecasting and Visualization, generating future predictions, reversing normalization for interpretation, and evaluating performance using metrics such as MAPE, MAD, and MSD.

Table 5 presents the forecasting performance (MAPE) for testing various ANN models with 1, 2, and 3 layers and different node configurations (10, 15, and 20) across each region. The results for different models within the same region are relatively close to one another.

TABLE 5. MAPE results for tested models of ANN Neural Network.

Layers	**1 Layer**			**2 Layers**			**3 Layers**		
Neuron	**100**	**150**	**200**	**100**	**150**	**200**	**100**	**150**	**200**
NW	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
AME	17.8 %	18.1 %	17.9 %	18.5 %	17.5 %	18.3 %	17.6 %	17.6 %	18.5 %
EUR	14.0 %	14.4 %	14.1 %	16.3 %	16.6 %	15.9 %	15.7 %	14.4 %	14.3 %
AFR	16.1 %	16.4 %	16.2 %	16.3 %	16.0 %	15.8 %	16.1 %	16.5 %	16.6 %
MNT	28.1 %	34.6 %	33.9 %	25.6 %	25.9 %	25.4 %	21.9 %	22.3 %	23.0 %
KSA	31.9 %	32.3 %	32.8 %	32.7 %	34.9 %	36.2 %	32.9 %	34.2 %	46.4 %
ISC	23.3 %	29.3 %	23.3 %	20.5 %	20.0 %	21.0 %	17.9 %	18.4 %	19.7 %
FES	19.1 %	18.8 %	21.1 %	18.3 %	18.3 %	18.3 %	18.1 %	17.9 %	17.9 %

The sample autocorrelations (ACF) and sample partial autocorrelations (PACF) of the differenced series for each region were examined to identify suitable ARIMA models. Residual analysis was conducted to evaluate the adequacy of these models. Table 2 presents the forecast accuracy metrices for selected models in each region, which were selected based on the absence of significant residual autocorrelations.

TABLE 6. Forecast accuracy metrics for selected models of ANN Neural Network.

Region	Selected Model	MAPE	MAD	MSD
AME	2 Layers, 15 Nodes	17.5%	182	60,485
EUR	1 Layer, 10 Nodes	14.0%	1,008	1,938,964
AFR	2 Layers, 20 Nodes	15.8%	396	224,818
MNT	3 Layers, 10 Nodes	21.9%	544	612,845
KSA	1 Layer, 10 Nodes	31.9%	383	258,794
ISC	3 Layers, 10 Nodes	17.9%	761	889,264
FES	3 Layers, 20 Nodes	17.9%	760	1,118,009

For each region, the Artificial Neural Network (ANN) model that demonstrated the highest level of performance was carefully selected based on a thorough evaluation of accuracy metrics. The detailed results, including the corresponding MAPE, MAD, and MSD values, are presented in Table 6.

The performance metric MAPE for all regions ranges between 14% and 32%. Each region utilized a uniquely selected model distinct from those of other regions, with most of the chosen models featuring 10 nodes but varying in the number of layers.

VII. Discussion

Accuracy metrics such as MAPE, MAD, and MSD were used to evaluate the forecasting models of each region, The best-performing model for each region, along with the selected models and their configurations, is presented in Table 7.

TABLE 7. MAPE Results for selected models across forecasting methods for each region.

Region	**Decomposition**	**ARIMA**	**LSTM Neural Network**	**ANN Neural Network**	**Best Method**	**Model**
AME	15%	12%	19%	18%	ARIMA	ARIMA(1,0,1) $(1,1,1)_{12}$
EUR	12%	8%	19%	14%	ARIMA	ARIMA(2,0,3) $(1,1,1)_{12}$
AFR	12%	10%	97%	16%	ARIMA	ARIMA(1,0,1) $(1,1,0)_{12}$
MNT	27%	24%	17%	22%	LSTM Neural Network	2 Layers, 150 Neurons
KSA	32%	30%	77%	32%	ARIMA	ARIMA(1,0,3) $(1,1,1)_{12}$
ISC	33%	23%	10%	18%	LSTM Neural Network	2 Layers, 100 Neurons
FES	14%	15%	15%	18%	Decompositi on	Multiplicative

Figures 1-7 present the time series plots for each region, displaying the actual monthly sales from 2018 to 2023 alongside the monthly forecasts for 2024 generated by the selected model.

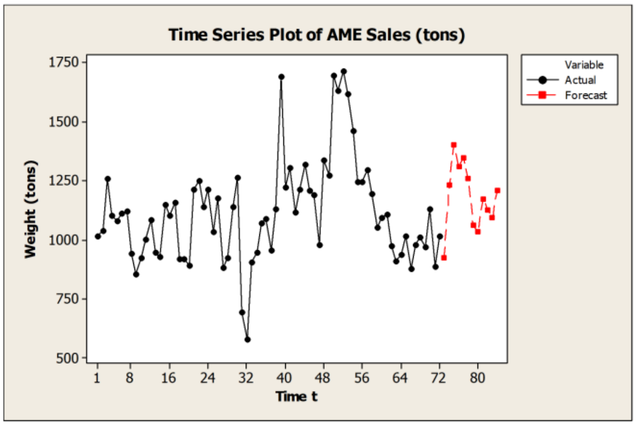

Fig. 1. Plot of actual and forecasts for AME Region.

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The forecasts for the AME region using ARIMA indicate a gradual upward trend while maintaining the seasonal pattern. In contrast, the EUR region exhibits a declining trend over the years, reflected in the gradual downward movement of ARIMA-based forecasts. The AFR region shows a consistent downward trend in forecasts using ARIMA, with actual values for 2023 and forecasts for 2024 gradually decreasing. AFR sales consistently peak in May, experience a significant dip in June, and then begin to rise in the subsequent months.

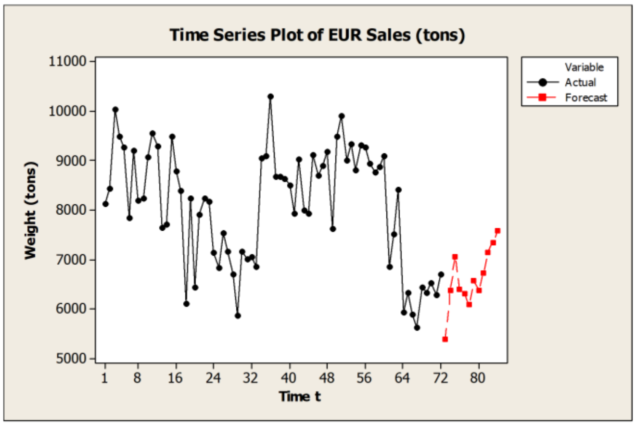

Fig. 2. Plot of actual and forecasts for EUR Region.

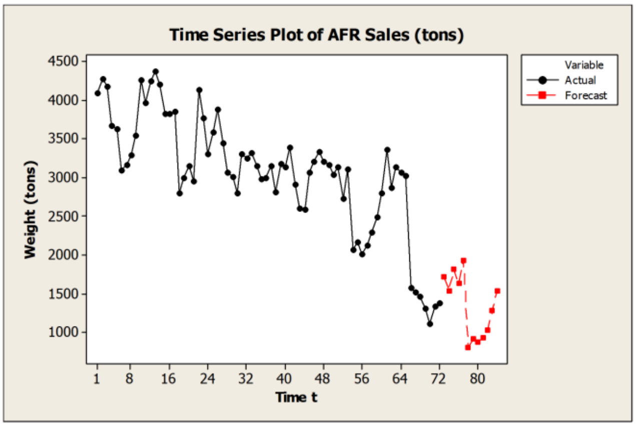

Fig. 3. Plot of actual and forecasts for AFR Region.

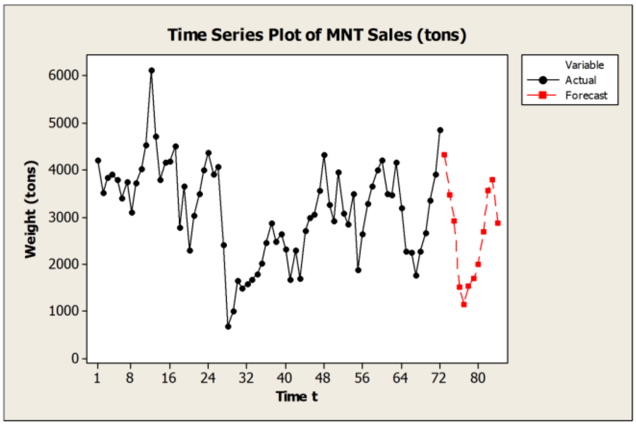

Fig. 4. Plot of actual and forecasts for MNT Region.

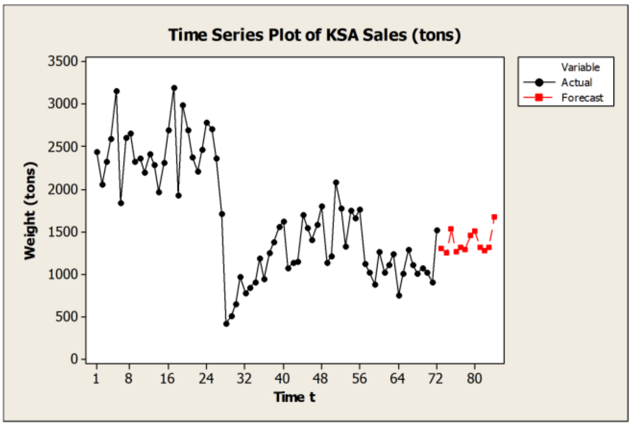

Fig. 5. Plot of actual and forecasts for KSA Region.

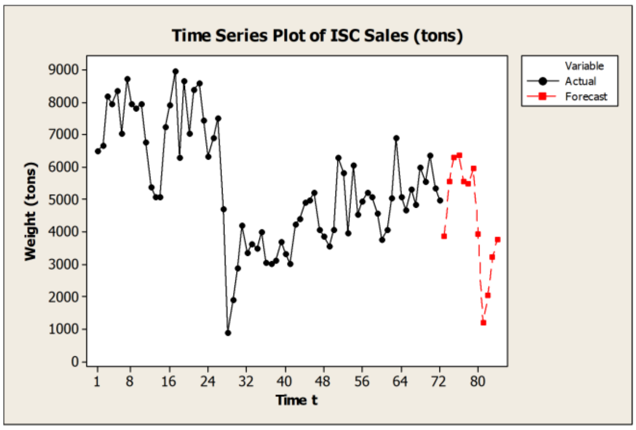

Fig. 6. Plot of actual and forecasts for ISC Region.

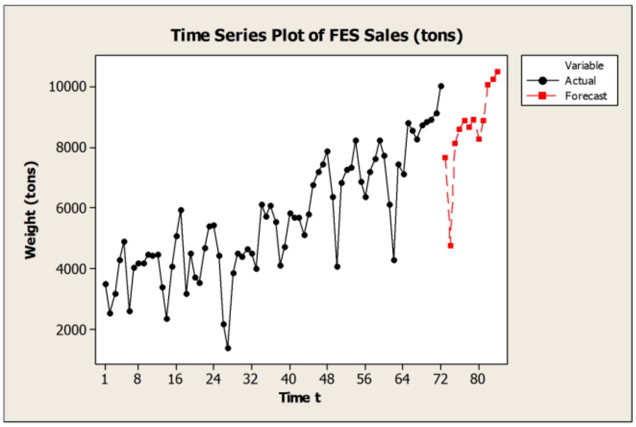

Fig. 7. Plot of actual and forecasts for FES Region.

The forecast plot for MNT sales effectively captures the observed trends using the LSTM neural network, particularly aligning with the sales behavior for 2023. The ARIMA-based forecasts for KSA sales in 2024 range between 1,400 and 1,700 tons, suggesting reduced variability compared to the fluctuations seen in previous years. Similarly, the ISC region forecasts for 2024, generated using the LSTM neural network, range between 4,600 and 6,000 tons, closely reflecting the observed trend of 2023. The forecasts for the FES region, derived using multiplicative decomposition, reveal a significant upward trend, with 2024 forecasts notably higher

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than those of previous years. Despite this growth, the seasonal pattern remains consistent, with February consistently marking the lowest demand.

The demand forecasts for each region were generated using the most appropriate forecasting model, selected based on historical data patterns and accuracy performance metrics. These regional forecasts were then aggregated to produce the overall demand forecast for the company. Each region was modeled independently to account for its unique characteristics, including distinct seasonality, trends, and export product profiles, ensuring a precise and tailored forecasting approach. The 2024 forecast, presented alongside the actual historical trend in figure 8, shows monthly forecasted sales ranging between 22,800 and 29,100 tons. This indicates minimal variation across months, reflecting stable and consistent forecasts. Furthermore, the seasonal patterns are well-maintained, as evident from lower sales projections in February, August, and September, which align with global air cargo market trends during these months.

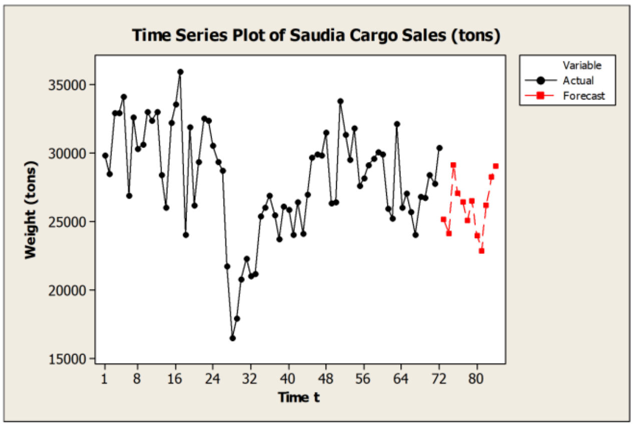

Fig. 8. Plot of actual and forecasts for Saudia Cargo Sales.

The total forecasted sales for Saudia Cargo in 2024 are projected to be 313,969 tons, representing a 4% decrease compared to the actual sales in 2023. This decline aligns with the gradual downward trend observed over the years, reflecting potential challenges such as shifting market dynamics, increased competition, and changes in global trade patterns.

VIII. Conclusion

This study conducted a detailed comparative analysis of forecasting methods to predict monthly air cargo demand for Saudia Cargo Company across seven regions, using historical data from 2018 to 2023 to forecast for 2024. The evaluation of ARIMA, time series decomposition, LSTM, and ANN models revealed that the optimal forecasting approach varied by region due to unique market dynamics. ARIMA models excelled in regions with stable trends (AME, EUR, AFR, KSA), while Neural Networks were more effective for regions with complex, non-linear patterns (MNT, ISC). Decomposition proved ideal for FES by effectively analyzing trend and seasonality components. However, ANN models underperformed, particularly in capturing seasonality. This study highlights the value of combining statistical and machine learning approaches for robust and adaptable demand forecasting. The findings highlight the importance of combining statistical and machine learning techniques to achieve robust, adaptable, and region-specific demand forecasting, offering valuable insights for efficient air cargo planning and operations.

Drawing from the analysis and findings of this study, the following recommendations are put forward to enhance forecasting accuracy and operational efficiency in air cargo demand management:

1) Adopt Region-Specific Forecasting Models: Customize forecasting methods to fit the unique dynamics of each region.
2) Continuous Model Validation: Establish a regular process to evaluate and validate forecasting models with updated data.
3) Investment in Forecasting Tools: Invest in advanced forecasting software and training for the analytics team to implement and manage sophisticated forecasting techniques like ARIMA and neural networks effectively.
4) Enhance Data Integration: Incorporate external variables such as economic indicators, weather patterns, and geopolitical events into the models.
5) Prioritize ARIMA as a Standardized Forecasting Tool: It simplifies the forecasting process, reduces the time required for model selection, and ensures a uniform methodology across the business.

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