Operations Analytics

Report

"Optimizing Forecasting and Inventory Management: Insights from Indigo T-Shirt Textiles Export Analysis"

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Introduction

This report provides a comprehensive analysis of forecasting, simulation, and profit calculations for Indigo T-shirt exports. Through decomposition analysis, seasonality, trend, and noise were identified within the quarterly export data. Among the three forecast models developed, Linear Exponential Smoothing (LES) with Seasonality emerged as the optimal choice, exhibiting a minimal Mean Absolute Percentage Error (MAPE) of 2.2% and a Root Mean Square Error (RMSE) of 6.955 against actual values.

The recommendation for maintaining a safety stock of 41,370 t-shirts aims to ensure efficient demand fulfilment and mitigate stock-out risks. Furthermore, simulation trials indicated an expected mean lead time demand of approximately 3,352,670 t-shirts. Considering future forecasts spanning ten quarters, a reorder point of 3,394,380 t-shirts is advised for optimal inventory management.

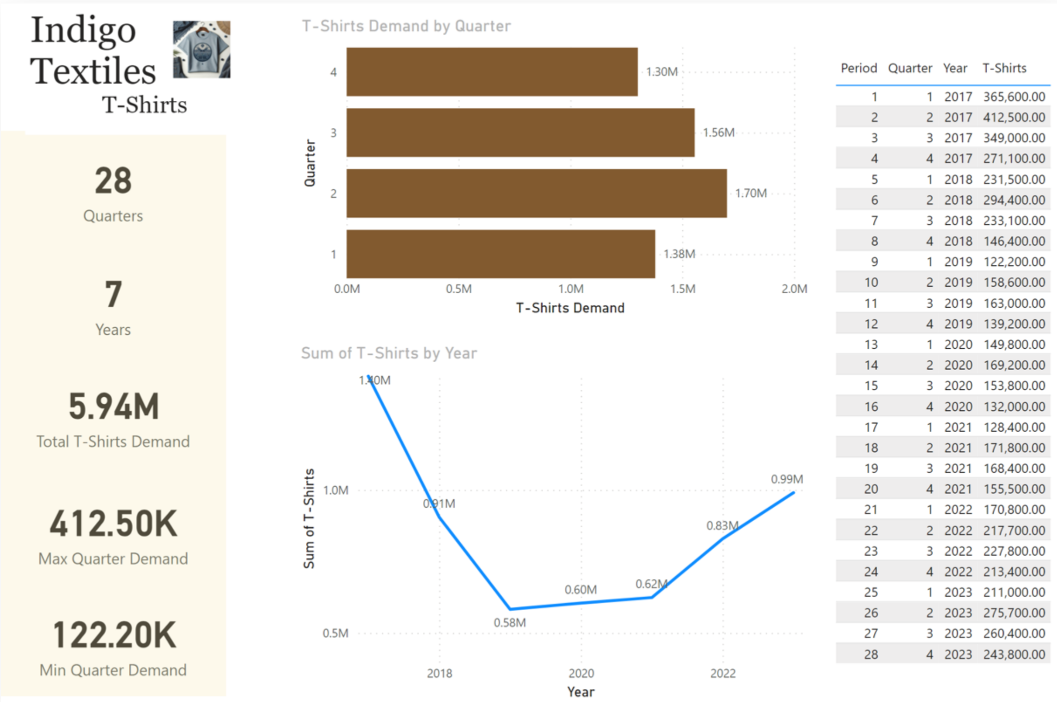
Moving forward, continuous monitoring of demand variability and refinement of the forecast model is advised to get the company to align its inventory operations with evolving market trends and demands.

Forecasting Approach and findings

Time series Exploration

The showcases the demand or production of Indigo Textiles T-Shirts. The dataset has a time frame from 2017 to 2023 with 28 quarters as seen in the Figure.1 below. Over 5.94 million T-Shirts were exported within the period with 412,500 being the maximum and 122,200 being the min exports recorded in a quarter.

Figure 1. Indigo Textiles T-Shirts Dashboard



Period	Quarter	Year	T-Shirts
1	1	2017	365,600.00
2	2	2017	412,500.00
3	3	2017	349,000.00
4	4	2017	271,100.00
5	1	2018	231,500.00
6	2	2018	294,400.00
7	3	2018	233,100.00
8	4	2018	146,400.00
9	1	2019	122,200.00
10	2	2019	158,600.00
11	3	2019	163,000.00
12	4	2019	139,200.00
13	1	2020	149,800.00
14	2	2020	169,200.00
15	3	2020	153,800.00
16	4	2020	132,000.00
17	1	2021	128,400.00
18	2	2021	171,800.00
19	3	2021	168,400.00
20	4	2021	155,500.00
21	1	2022	170,800.00
22	2	2022	217,700.00
23	3	2022	227,800.00
24	4	2022	213,400.00
25	1	2023	211,000.00
26	2	2023	275,700.00
27	3	2023	260,400.00
28	4	2023	243,800.00

The dataset's descriptive statistics below offer insights into the centrality and variations of T-shirt exports.

Table 1. Descriptive_Statistics

T-Shirts (000's)	
Mean	212.0035714
Standard Error	14.3266037
Median	191.4
Mode	#N/A
Standard Deviation	75.80926105
Sample Variance	5747.044061
Kurtosis	0.657080297
Skewness	1.077694942
Range	290.3
Minimum	122.2
Maximum	412.5
Sum	5936.1
Count	28
Largest(1)	412.5
Smallest(1)	122.2
Confidence Level(95.0%)	29.39576267

Measures of central tendency

Mean: On average, 212,000 T-Shirts were sold across the 7 years.

Median: When the exports are arranged in ascending order, the middle value is 191,400 units.

Measures of Variation

Standard Deviation: T-shirt export volumes vary by around 75,809 units from the average export volume of 212,000 units. A higher standard deviation implies greater variability in export volumes.

Sample Variance: On average, each data point differs from the mean by approximately 5,747 units squared. It gives a measure of the spread of the data points around the mean.

Range: A range of 290,300 units which is the difference between the maximum and minimum export values in the dataset. This shows the extent of variation in export volumes observed over the observed periods.

Kurtosis: A kurtosis of approximately 0.657 suggests the exports distribution is moderately peaked. It gives insight into the shape of the distribution; positive values indicate a relatively peaked distribution, while negative values suggest a flatter distribution.

Skewness: A skewness of around 1.078 indicates that the export distribution is positively skewed, meaning it has a longer right tail. This suggests that there are more extreme values on the higher end of the export volume spectrum compared to the lower end.

Coefficient of variation: The coefficient of variation (CV) of 35.76% for T-shirt exports indicates a moderate level of variability around the average export volume of 212,000 units. This suggests some fluctuation in export volumes over the observed periods, but not excessively high variability.

Classical Decomposition

Having explored the time series (T-Shirt exports), forecasting models were built to better predict future exports to guide operations. To do that, seasonality, trend, and noise shown in the data had to be separated (decomposed).

Process of Classical Decomposition

Trend

Centred-Moving Average with a window size of 4 quarters (CMA-4) was used to smooth the exports, reducing noise, and highlighting the trend. Both past and future exports were considered resulting in a more centred and balanced smoothing effect.

Figure 2. Trend_(CMA-4)

Figure.2 shows there was a declining trend in T-Shirt exports from 2017 to 2019 where exports stabilized through to 2021. Then an upward trend continues from 2021 1st Quarter through to 2023.

Seasonality

Figure.3 shows the exports when the trend is removed.

Figure 3. Detrended_T-Shirts_Exports

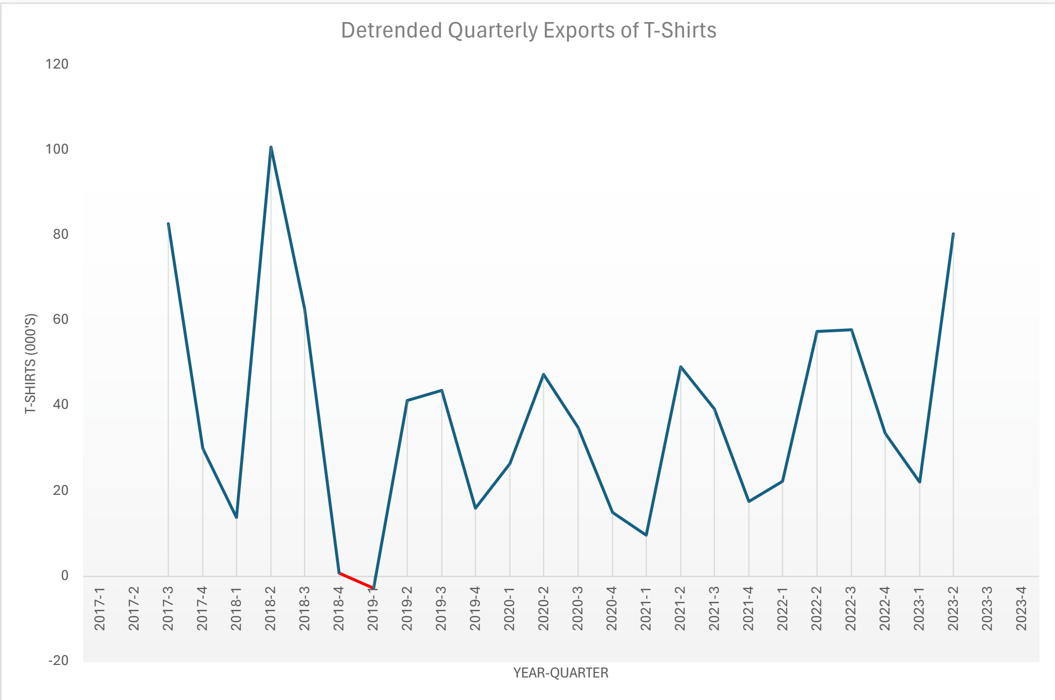


Figure.3 shows a recurring decline pattern every 3rd Quarter through 4. With this, the detrended data was aggregated by quarters and the average of the values across the years was calculated to identify quarterly seasonal profile shown below.

Figure 4. Seasonal_Profile

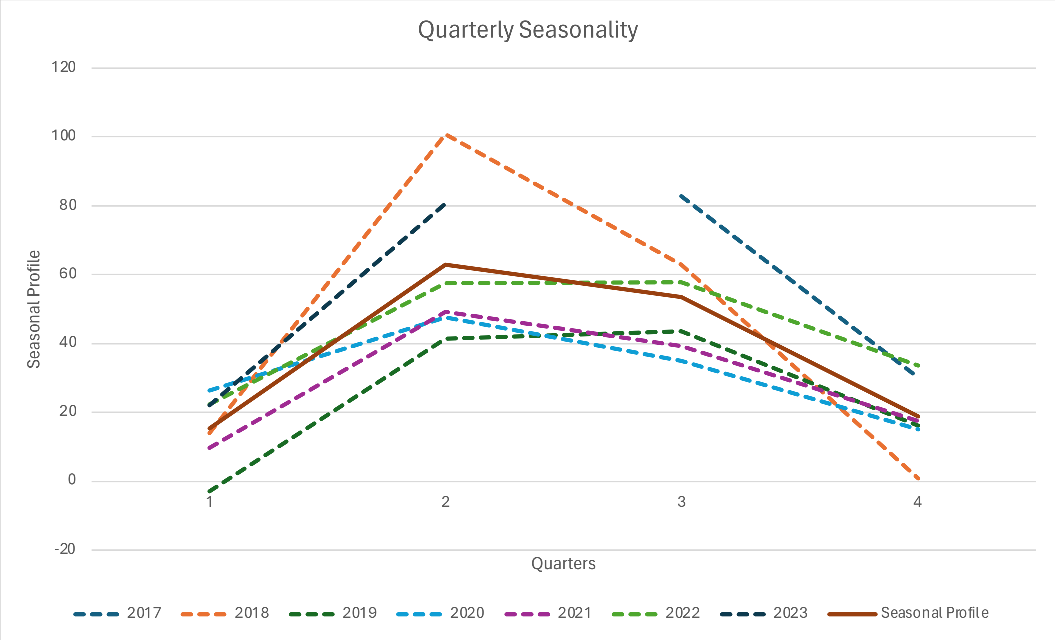
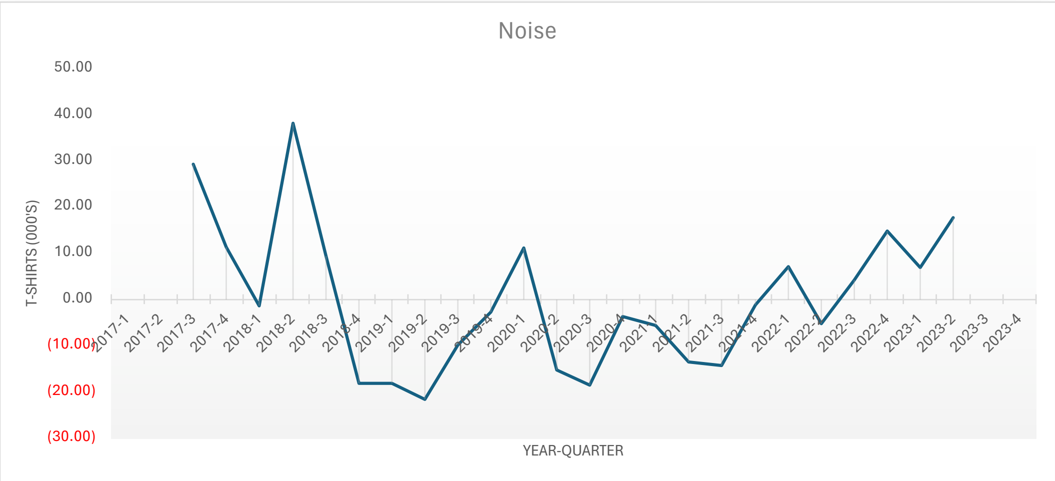


Figure.4 shows seasonality confirming that exports peaking every 2nd Quarter then declines in 3rd Quarter then falls back in 4th Quarter.

Noise

To identify the noise, the seasonal profile was matched to each quarter using vlookup function in excel. The trend and seasonality was added, then subtracted from the time-series to show the noise depicted in Figure.5 below.

Figure 5. Noise



Random fluctuations in the exports which cannot be attributed to any underlining pattern or trend in exports is illustrated in Figure.5.

Time series model building

Process of Model building

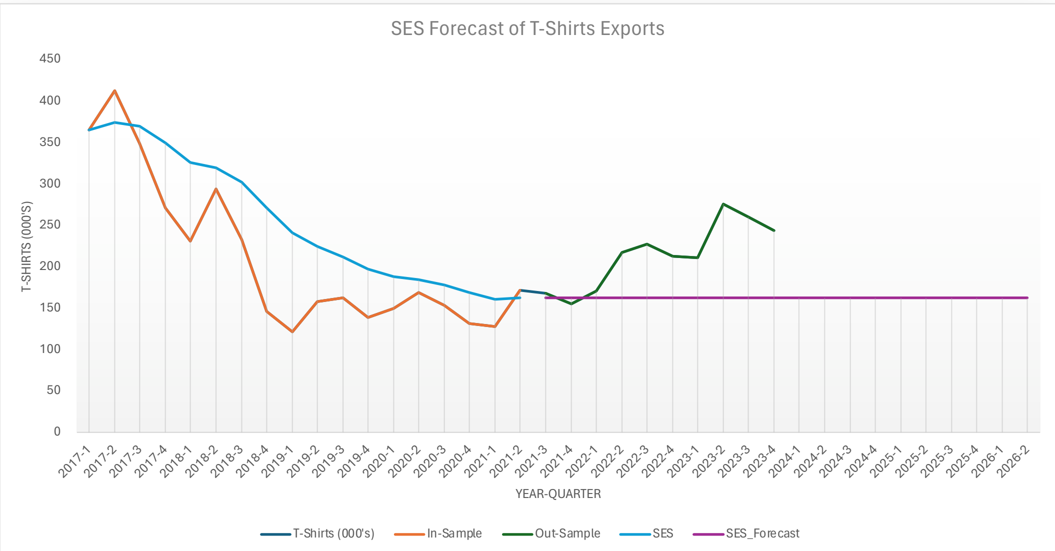
The dataset was divided into in-sample and out-sample sets, with 18 observations (about 64%) allocated to the in-sample set for model training and 10 observations (about 36%) reserved for out-sample testing. This division is crucial for utilizing the training set to build models and estimate parameters, while the test set independently evaluates the model's performance, ensuring accuracy and guarding against overfitting. The three models built are explained below.

1. *Simple Exponential Smoothing (SES)*

Specification and Parameters:

Firstly, SES was used to smooth the time series by exponentially decreasing the weight of past export observations using a parameter of 0.2 while giving higher weight to recent observations using 0.8.

Figure 6. SES_Forecast



Pros

Using only one parameter makes using SES simple and easy. When trend and seasonality in a time series is not clear, SES can be used as it effectively smoothens out random noise.

Cons

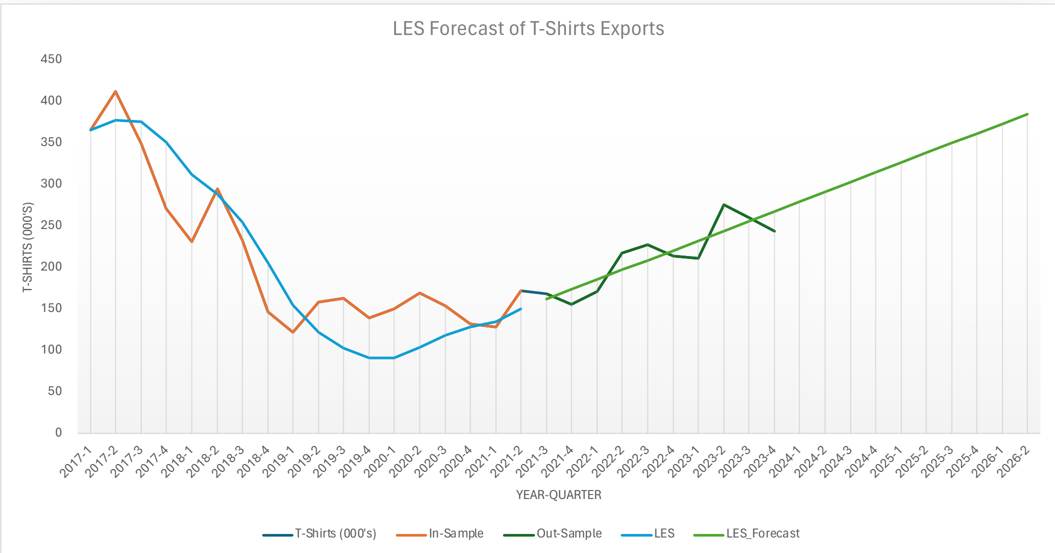
Its use of only one parameter limits its ability to capture complex patterns. Also, using a constant level of smoothing across all observations is not realistic.

2. *Linear Exponential Smoothing (LES)*

Specification and Parameters:

Secondly, LES was used to extend the SES model with a trend component using a beta. The alpha was adjusted from 0.2 to 0.25 to smooth the level while a beta of 0.53 was used to smooth out the trend alongside.

Figure 7. LES_Forecast



Pros

This is better than SES as it captures a linear trend in the model. Both alpha and beta can be adjusted to adapt to changing trend patterns.

Cons

With a fixed trend, LES fails when there is a non-linear trend in the level. It had to be carefully tuned to arrive at alpha-2 and beta-0.25 took time as LES is sensitive to them.

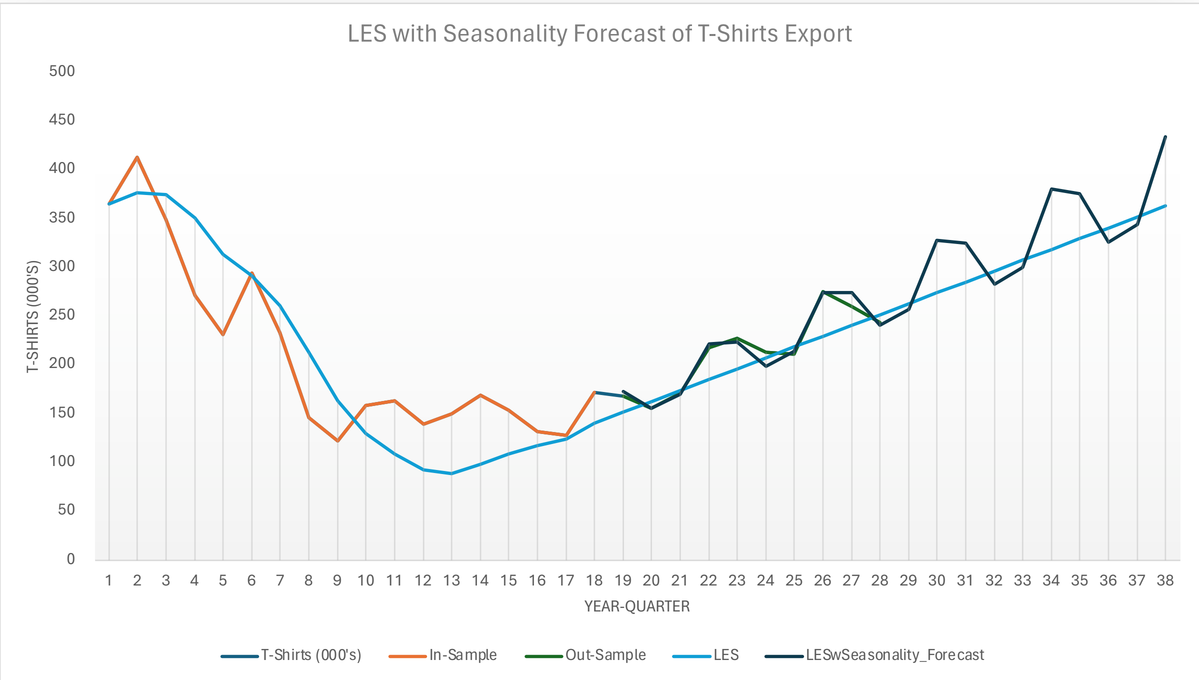
3. Linear Exponential Smoothing with Seasonality (LESwS)

Specification and Parameters:

Since seasonality was identified in the level above, winter's method which is a special case for forecasting was used as it captures seasonality thus improving on LES.

Alpha and beta were adjusted to 0.242 and 0.474 respectively for the LES and the seasonality incorporated multiplicatively to build the model.

Figure 8. LES_Seasonality



Pros

It captures both trend and seasonality patterns which LES and SES fails to. When seasonal patterns changes, this model can adjust to it. It therefore creates the best forecast model among the three.

Cons

Just like LES, it assumes a linear trend and seasonality and it fails at non-linear patterns. Tripled with seasonality, finetuning and estimating the parameters are even more tricky. It's sensitivity to the parameters affects its forecast accuracy.

Time series forecasting

Based on the forecasting models, the LES with Seasonality proved to be the best model. Here are the error metrics and discussion to prove so.

SES Error Metrics

The SES model forecasts consistently over/underestimated exports by 51,350 units (bias). The error averaged at 52,870 units with a 22% MAPE.
It recorded a high MSE (4079.60) and RMSE (63.87) indicating significant variations in forecast errors.

Table 2. SES_Error_Metrics

Bias (Error)	MAD	MAPE	MSE	
5.30	5.30	3%	28.10	
-7.60	7.60	5%	57.75	
7.70	7.70	5%	59.30	
54.60	54.60	25%	2981.22	
64.70	64.70	28%	4186.16	
50.30	50.30	24%	2530.15	
47.90	47.90	23%	2294.46	
112.60	112.60	41%	12678.88	
97.30	97.30	37%	9467.40	
80.70	80.70	33%	6512.58	
51.35	52.87	22%	4079.60	
			RMSE	**63.87174254**

LES Error Metrics

The LES showed an improvement over the SES model. The bias dropped to -2,200 indicating the LES model generally forecasts close to the actual export volumes unlike the consistent over/underestimation of SES.

The Mean Absolute Deviation (MAD) of 16.73 and Mean Absolute Percentage Error (MAPE) of 8% are significantly lower compared to SES, suggesting smaller average errors in absolute terms and percentages.

The Mean Squared Error (MSE) of 345.91 and Root Mean Squared Error (RMSE) of 18.60 are also considerably lower than SES, indicating less overall spread and smaller typical errors in the forecasts.

Table 3. LES_Error_Metrics

Bias (Error)	MAD	MAPE	MSE	
6.64	6.64	4%	44.11	
-18.02	18.02	12%	324.62	
-14.48	14.48	8%	209.55	
20.67	20.67	9%	427.06	
19.01	19.01	8%	361.25	
-7.15	7.15	3%	51.15	
-21.31	21.31	10%	454.15	
31.63	31.63	11%	1000.50	
4.57	4.57	2%	20.90	
-23.79	23.79	10%	565.81	
-0.22	16.73	8%	345.91	
			RMSE	**18.59865369**

LESwS Error Metrics

The LES with Seasonality showed a very promising level of accuracy. The near-zero bias (-0.05) which represents just an error of 500 units suggests the LES model with seasonality forecasts extremely close to the actual export volumes on average.

Table 4. LESwS_Error_Metrics

Bias (Error)	MAD	MAPE	MSE	
-4.45	4.45	2.64%	19.78	
-0.31	0.31	0.20%	0.10	
0.66	0.66	0.39%	0.43	
-3.70	3.70	1.70%	13.71	
4.35	4.35	1.91%	18.94	
15.09	15.09	7.07%	227.61	
-2.59	2.59	1.23%	6.71	
1.15	1.15	0.42%	1.33	
-13.65	13.65	5.24%	186.26	
2.98	2.98	1.22%	8.91	**RMSE**
-0.05	4.89	2.20%	48.38	**6.955**

This is a significant improvement over any potential bias observed in previous models.
Both the MAD of 4.89 and MAPE of 2% are very low. This signifies that the model's forecasts typically deviate from the actual exports by a very small amount, both in absolute terms (units) and as a percentage of the actual value.
The MSE of 48.38 and RMSE of 6.96 are also very low. This indicates minimal spread and very small typical errors in the forecasts.

The discussions above accompanying the errors metrics therefore shows that SES with Seasonality is the best model.

Safety Stock

To determine the safety stock, first, the Z-score corresponding to a service level of 97% was calculated, resulting in a value of 1.88. Next, the square root of the expected lead time of 10 quarters was obtained, yielding a value of 3.16. Then, utilizing the RMSE of 6.96 obtained from the LES with seasonality model, these three factors were multiplied together to derive the safety stock of 41.37 (41,370 t-shirts).

The safety stock requirement of approximately 41,370 units ensures effective customer demand fulfilment while minimizing stockout risks, aligning with the desired 97% service level. Incorporating lead time and forecast accuracy enhances the robustness of the safety stock calculation, contributing to a reliable inventory management system. Overall, this approach yields actionable insights for optimizing inventory levels and meeting customer demand efficiently.

Simulation Approach and Findings

Expected Lead Time Demand for the company.

To simulate the expected lead time demand for the company, a robust approach was taken. This involved generating 150 random probabilities to encompass all potential outcomes. The mean and standard deviation of lead time demand (3,353), obtained from 10 forecasts, were then applied using the Excel function =NORM.INV.

Table 5. Forecasted_Exports

Week after order	Quarter	Forecast
1	2024-1	257
2	2024-2	328
3	2024-3	325
4	2024-4	283
5	2025-1	300
6	2025-2	381
7	2025-3	375
8	2025-4	326
9	2026-1	344
10	2026-2	434
		3,353

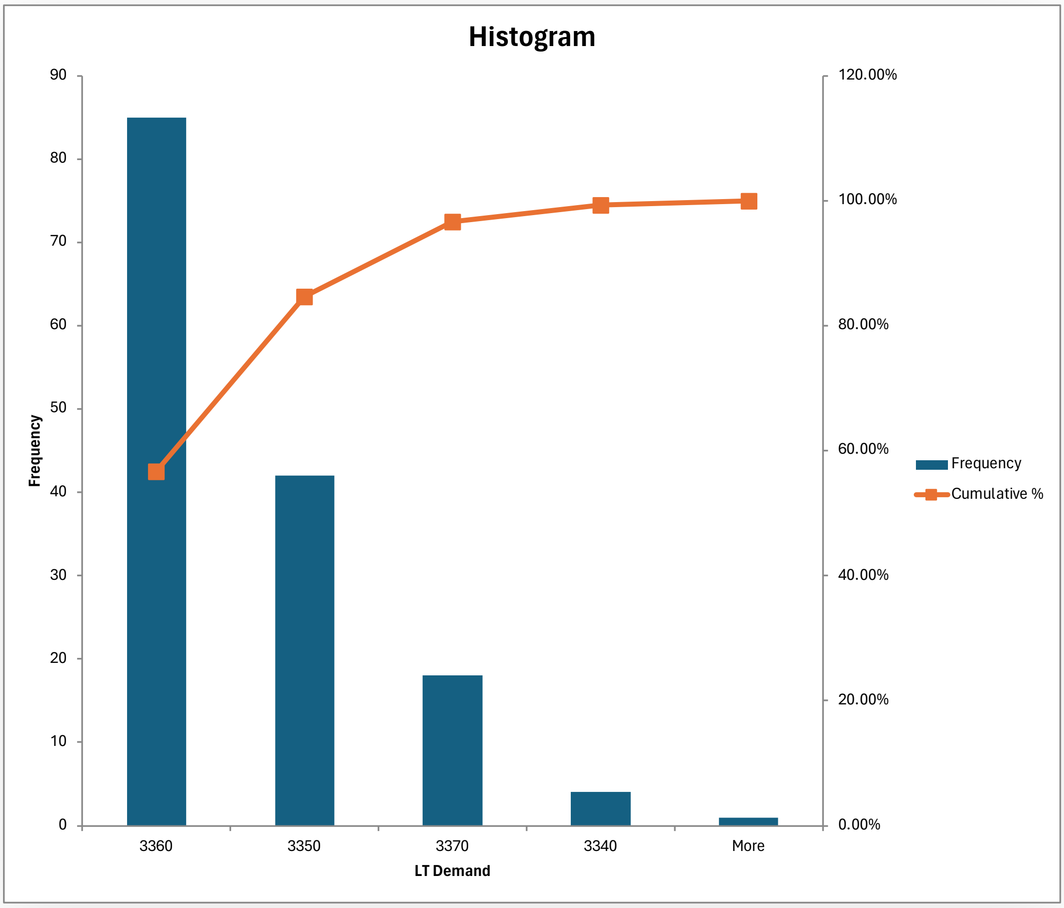
Expected Value of Lead-Time Demand

This function, utilizing probability, mean, and standard deviation, provided an estimate of expected lead time demand. The resulting distribution captured the variability in forecasts. Finally, the mean of all simulated lead time demands shown in Table.6 below was calculated, offering insights into the company's expected lead time demand.

Table 6. Mean_of_LT_Demand(Simulation)

Expected Lead Time Demand	**3,353**	*T-Shirts over 10 Quarters*
St. Dev of LT Demand	**6.96**	*T-Shirts over 10 Quarters*
Mean of LT Demand (Simulation)	**3,352.96**	*T-Shirts over 10 Quarters*

Figure 9. Histogram_of_LT_Demand



In figure.9, the histogram generated for an instance of simulated values was right-skewed, indicating that most Lead Time demand (LTD) values are concentrated at the lower end. The highest frequency occurs at the leftmost bins, suggesting that lower LTD values are more common. The business can use this information to plan their inventory. Focusing on meeting demand during peak periods is crucial. Also understanding the distribution helps assess the risk of stockouts or excess inventory.

Expected profit for the company.

Before computing the expected profit, the inherent uncertainty surrounding the company's share of the expected lead-time demand was addressed. To tackle this uncertainty, random probabilities of the potential share of demand belonging to the company were generated. Subsequently, the simulated lead time (LT) demand was multiplied by the LT demand share to determine the total T-shirts demand. Leveraging a selling price of £8 and variable cost of £4.50 per unit, the profit was then calculated. This comprehensive approach ensured a thorough examination of potential profit outcomes, considering the variability in demand share and associated costs.

Figure 10. Company_Risk_Profile

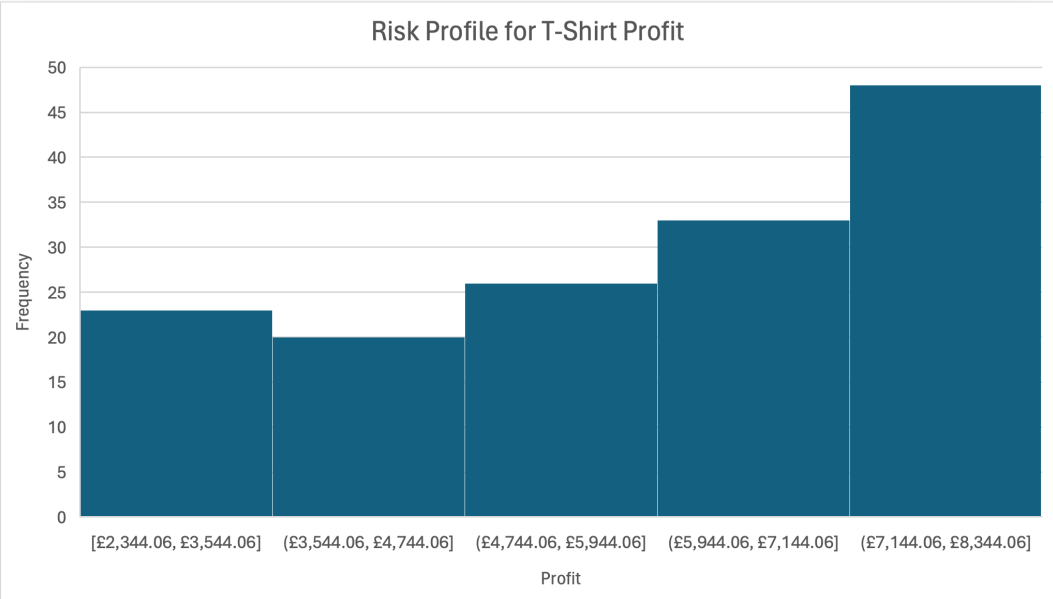


Figure.10 shows the profit risk profile to the company based on the LT Demand of an instance of simulation. The histogram displays the frequency of different profit ranges. The rightmost bars represent higher profits, but they occur less frequently compared to the combined frequencies of the rest. The leftmost bars indicate lower profits, which are more common and could imply the company faces a greater risk when aiming for profit as those outcomes are less likely.

Conclusion and Recommendation

Throughout this analysis, comprehensive methodologies were employed to forecast future T-Shirt exports, simulate lead time demand, and calculate expected profit for the company. Key findings reveal the importance of robust forecasting models and careful consideration of uncertainty in demand projections. The safety stock calculations highlighted the necessity of maintaining approximately 41,370 units to balance customer satisfaction and inventory costs.

Additionally, the simulation of lead time demand yielded a mean of about 3,352,960 units, emphasizing the need for agile inventory management strategies. Furthermore, profit calculations demonstrated the significance of accurate demand estimation, with potential profits calculated based on a selling price of £8.00 and a variable cost of £4.50 per unit.

In conclusion, the integration of forecasting, simulation, and profit analysis offers actionable insights for optimizing inventory levels, enhancing operational efficiency, and ultimately driving business success. It is recommended that more simulations are run beyond 150 trials (>500) to get more accurate estimations of key metrics such as expected demand and profit which will boost confidence levels in obtained results; to better identify and mitigate risks associated with inventory management and planning to enhance overall risk management. It is also recommended that the company continues to refine its forecasting models, monitor demand variability, and adapt inventory management strategies accordingly to maintain a competitive edge in the market.