Winter Rock Business Report

Introduction

To create methods for controlling future demand in the winter sports industry, this paper examines historical and present market data from Winter Rock. In particular, it looks at seasonal sales patterns, projects demand for year-round items, improves distribution strategies, and assesses potential suppliers for the introduction of a new ski product.

To begin with, we look at overall sales data from January 2019 to June 2022 to spot seasonal trends and guide capacity planning during busy times. The report then uses Single Exponential Smoothing to estimate sales of year-round items, allowing Winter Rock to control the anticipated winter demand spike while keeping inventory levels stable.

A distribution plan is presented to minimize shipping costs across Winter Rock's two distribution centres, balancing regional demand with available capacity. To provide the best sourcing plan, we further evaluate possible suppliers for a new, reasonably priced ski product using decision tree modelling and numerous profit scenarios. Finally, a simulation evaluates how changing sales demand affects the new skis' profitability.

This thorough research leads us to several recommendations, including coordinating marketing and manufacturing with seasonal trends, improving inventory control, streamlining distribution to cut costs, and choosing a supplier that will balance risk and maximise projected revenue.

Section 2: Investigating Sales Trends

a) Plot of Original Time Series Data and 12-Month Centred Moving Average

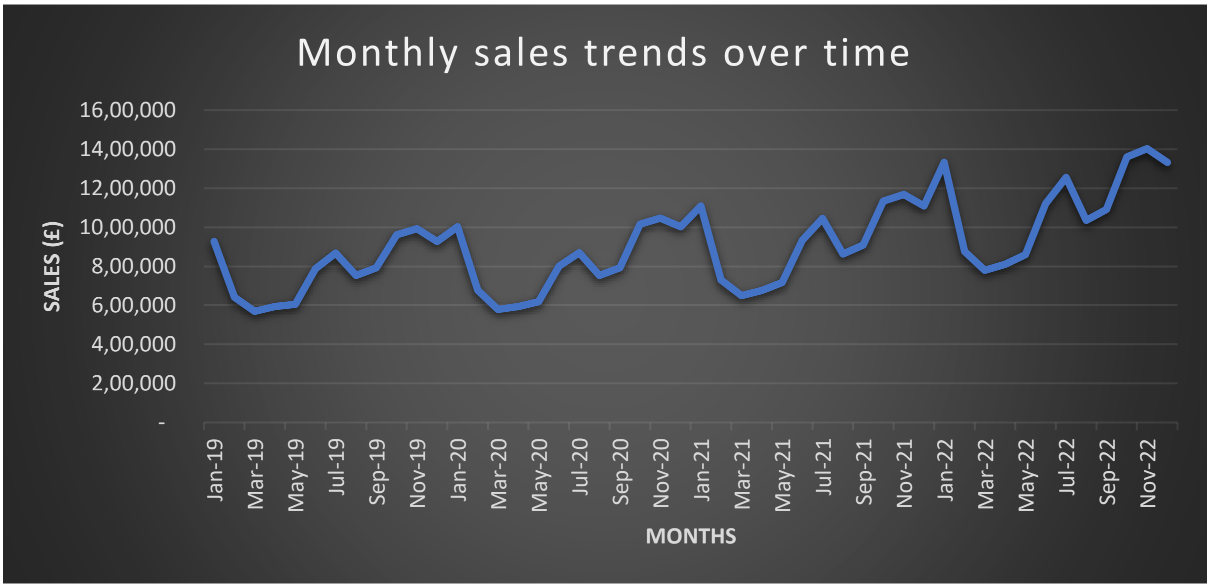


Figure 1: Original Monthly sales time-series chart

Winter Rock's initial monthly sales figures, which covers the period from January 2019 to December 2022, show varying total sales values of £5,69,679 (March 19) to £14,03,067 (November 22). Seasonal peaks, which show patterns of demand for winter activities, are mostly seen in the months preceding the winter season.

How the 12-Month Centred Moving Average Is Calculated (Singh, 2020)

The formula used for this calculation is: MAt=AVERAGE (Bt−6: Bt+5), where MAt represents the moving average at month t and Bt is the sales figure at month t, requiring sufficient data on either side and thus not applicable to the first and last six months of the dataset.

The long-term trend is more clearly seen while monthly swings are less noticeable thanks to the centred moving average. The data show a clear increase trend in total demand from June 19 with a centred moving average of £7,85,238 to June 22 with a moving average of £11,04,831.

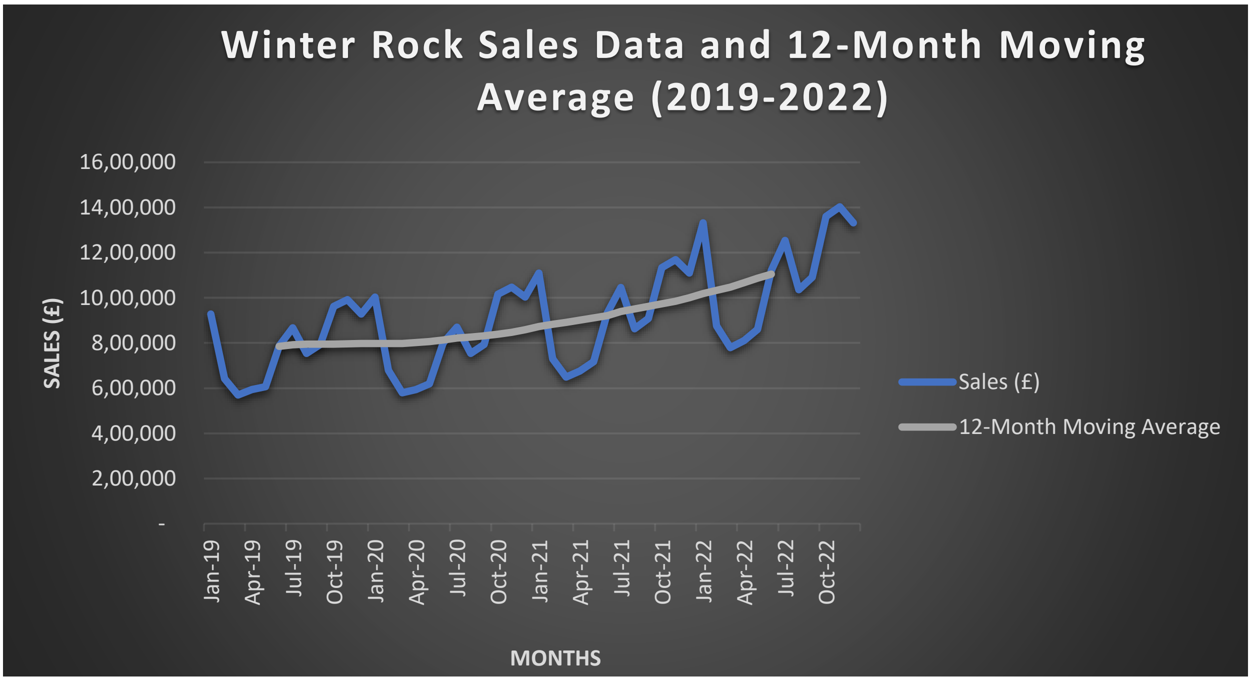


Figure 2: The graph shows the 12-month moving average from 2019 to 2022 together with the Winter Rock sales data.

The blue line represents monthly Winter Rock sales (£) from 2019 to 2022, showing seasonal fluctuations.

- The grey line is the 12-month moving average, smoothing short-term variations to reveal an overall upward sales trend.

b) Detrended Monthly Values and Seasonal Matrix

By calculating the monthly aggregate sales statistics using a 12-month centred moving average, we were able to detect seasonal fluctuations and get insight into Winter Rock's sales data patterns.

Formula Applied: Detrended Salest = Salest − 12-Month Moving Averaget; where t is the month.

We were able to see the seasonal variations in the trend by deducting the centering moving average from the initial values to get the monthly sales. In October 2020, for example, the detrended value was £1,83,952 above the norm, suggesting a noteworthy seasonal high before the winter sports season.

Period	Sales (£)	12-Month Moving Average	Detrended Sales (£)	Year	Month
Jan-19	9,27,616			2019	1
Feb-19	6,42,223			2019	2
Mar-19	5,69,679			2019	3
Apr-19	5,94,002			2019	4
May-19	6,05,950			2019	5
Jun-19	7,87,416			2019	6
Jul-19	8,67,448	7,85,238	82,210	2019	7
Aug-19	7,53,375	7,91,521	- 38,146	2019	8
Sep-19	7,93,026	7,94,544	- 1,518	2019	9
Oct-19	9,62,370	7,95,344	1,67,026	2019	10
Nov-19	9,92,133	7,95,344	1,96,789	2019	11
Dec-19	9,27,616	7,96,482	1,31,134	2019	12
Jan-20	10,03,017	7,97,558	2,05,459	2020	1
Feb-20	6,78,494	7,97,773	- 1,19,279	2020	2
Mar-20	5,79,280	7,97,773	- 2,18,493	2020	3
Apr-20	5,94,002	7,97,773	- 2,03,771	2020	4
May-20	6,19,605	8,02,257	- 1,82,652	2020	5
Jun-20	8,00,325	8,06,880	- 6,555	2020	6
Jul-20	8,70,030	8,13,163	56,867	2020	7
Aug-20	7,53,375	8,22,092	- 68,717	2020	8
Sep-20	7,93,026	8,26,360	- 33,334	2020	9
Oct-20	10,16,179	8,32,227	1,83,952	2020	10
Nov-20	10,47,607	8,39,054	2,08,553	2020	11
Dec-20	10,03,017	8,47,162	1,55,855	2020	12
Jan-21	11,10,167	8,58,349	2,51,818	2021	1
Feb-21	7,29,701	8,72,979	- 1,43,278	2021	2
Mar-21	6,49,689	8,82,147	- 2,32,458	2021	3
Apr-21	6,75,932	8,91,798	- 2,15,866	2021	4
May-21	7,16,897	9,01,629	- 1,84,732	2021	5
Jun-21	9,34,572	9,11,763	22,809	2021	6
Jul-21	10,45,582	9,20,692	1,24,890	2021	7
Aug-21	8,63,396	9,39,195	- 75,799	2021	8
Sep-21	9,08,837	9,51,357	- 42,520	2021	9
Oct-21	11,34,146	9,62,185	1,71,961	2021	10
Nov-21	11,69,222	9,73,451	1,95,771	2021	11
Dec-21	11,10,167	9,85,399	1,24,768	2021	12
Jan-22	13,32,201	10,00,975	3,31,226	2022	1
Feb-22	8,75,642	10,18,402	- 1,42,760	2022	2
Mar-22	7,79,627	10,32,792	- 2,53,165	2022	3
Apr-22	8,11,119	10,47,939	- 2,36,820	2022	4
May-22	8,60,277	10,66,842	- 2,06,565	2022	5
Jun-22	11,21,487	10,86,329	35,158	2022	6
Jul-22	12,54,699			2022	7
Aug-22	10,36,076			2022	8
Sep-22	10,90,605			2022	9
Oct-22	13,60,976			2022	10
Nov-22	14,03,067			2022	11
Dec-22	13,32,201			2022	12

Table 1: Detrended Monthly Sales Values

Seasonal Matrix

The detrended numbers were combined into a matrix to display monthly fluctuations over multiple years. This matrix reveals patterns that are constant.

Average of Detrended Sales (£)	**Column Labels**				
Row Labels	**2019**	**2020**	**2021**	**2022**	**Grand Total**
1		205459.4167	251817.6667	331225.75	262834.2778
2		-119278.75	-143277.6667	-142759.6667	-135105.3611
3		-218492.75	-232458.0833	-253164.6667	-234705.1667
4		-203770.75	-215866	-236820	-218818.9167
5		-182651.8333	-184731.5833	-206564.5	-191315.9722
6		-6554.666667	22808.83333	35158.41667	17137.52778
7	82210.16667	56866.91667	124889.6667	149867.5833	103458.5833
8	-38146.25	-68717.25	-75799.16667		-60887.55556
9	-1517.833333	-33333.5	-42519.91667		-25790.41667
10	167026.0833	183952.0833	171960.9167		174313.0278
11	196789.0833	208552.5833	195771.3333		200371
12	131134.1667	155854.9167	124768		137252.3611
Grand Total	**89582.56944**	**-1842.798611**	**-219.6666667**	**-46151.0119**	**5126.722973**

Table 2: Detrended values seasonal matrix

Across all years, the detrended data show sales peaks in January and October-November. For example, the detrended value was £2,05,459 over trend in January 2020 and £1,71,961 in October 2021, indicating significant seasonal peaks before the winter sports season. On the other hand, sales often decrease after this peak; detrended statistics such as -£1,19,279 (Feb-20) and -£2,32,458 (Mar-21) demonstrate that demand was weaker in the spring and summer.

c) Annual Seasonal Profile and Median Seasonal Profile

The annual profiles for 2019, 2020, 2021, and 2022 follow similar patterns, reflecting significant seasonal trends. The peak months consistently occur around January and October-November, showing heightened sales activity in the winter sports season. For instance, January 2022 displays a detrended value of £3,31,225.75, while October 2022 reaches £1,71,960.92. The troughs are typically observed in spring and summer months like March and April, such as -£2,53,164.67 (Mar-22).

The median profile, depicted in purple, highlights the central trend across all years and smooths out annual fluctuations to offer a comprehensive seasonal view. For instance, the median detrended value in January is £2,51,817.67, while in October, it is £1,71,960.92.

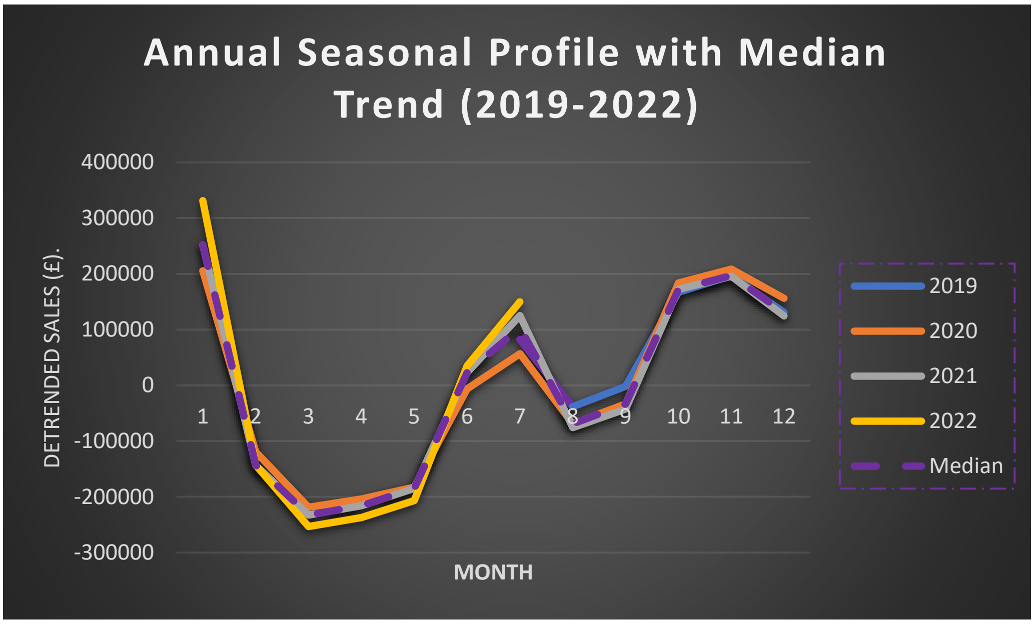


Figure 3: Annual seasonal Profile with Median time series chart

Seasonal Matrix:

Month	2019	2020	2021	2022	Median
1		205459.417	251817.667	331225.75	251817.667
2		-119278.75	-143277.667	-142759.667	-142759.667
3		-218492.75	-232458.083	-253164.667	-232458.083
4		-203770.75	-215866	-236820	-215866
5		-182651.833	-184731.583	-206564.5	-184731.583
6		-6554.66667	22808.8333	35158.4167	22808.8333
7	82210.1667	56866.9167	124889.667	149867.583	103549.917
8	-38146.25	-68717.25	-75799.1667		-68717.25
9	-1517.83333	-33333.5	-42519.9167		-33333.5
10	167026.083	183952.083	171960.917		171960.917
11	196789.083	208552.583	195771.333		196789.083
12	131134.167	155854.917	124768		131134.167

Table 3: Detrended values seasonal matrix with median

High demand consistently occurs in January and October-November, suggesting a pre-winter sales boost, while troughs are observed in March and April, aligning with the reduced demand in spring and summer. Understanding these patterns allows Winter Rock to align its production, distribution, and promotional strategies to seasonal demand, ensuring efficient operations and optimized sales.

d) Trends and Seasonality

The time series data shows a clear trend of fluctuating demand for year-round products, with noticeable peaks around winter and Christmas, reflecting seasonal variations. The forecasts also reveal some periods of steady growth and contraction, suggesting cyclical demand patterns.

e) Implications for Capacity Planning and Marketing

Given the seasonal spikes in winter, Winter Rock should ramp up production and distribution capacity before the Christmas season to prevent stockouts. Marketing campaigns should align with peak demand periods to maximize sales. Accurate forecasts can help refine inventory management, ensuring optimal stock levels year-round while minimizing excess inventory.

Section 3: Forecasting Sales of Year-Round Products

a) Forecasting using Single Exponential Smoothing (SES)

Forecasts made one step ahead of time with Single Exponential Smoothing (SES) (Athanasopoulos, 2018)

Step 1: To calculate the forecast value, create two new columns: one for "Alpha" and another for "Forecast."

Step 2: Select an alpha (α) value in step two. Employing (α) = 0.55 to get the best answers.

Step 3: Enter the actual sales figure for the first month in the first row of the forecast column. Start entering the SES formula on the second row:

Forecasting Formula: Alpha * Previous predicted value * actual sales value + (1 - ALPHA) *

Until June 22, drag and copy the formula to the remaining cells.

D3 | fx = C3* B3 + (1 - C3) * D2

	A	B	C	D
1	Period	Sales (£)	Alpha	Forecast
2	Jan-19	3,78,052	0.55	378052.00
3	Feb-19	3,95,196	0.55	387481.20
4	Mar-19	3,64,619	0.55	374906.99
5	Apr-19	3,83,309	0.55	379528.10

Step 4: To evaluate the accuracy, more columns were made to compute error metrics like Mean Absolute Error (MAE) or Mean Squared Error (MSE), as well as the difference between actual sales and anticipated figures.

- Errors in the formula are (Actual - Forecast).
- ABS(Errors) is the absolute error.

- Errors^2 = Squared Errors.

Period	Sales (£)	Alpha	Forecast	Error E	Absolute Error(AE)	Squared Error(SE)
Jan-19	3,78,052	0.55	378052.00	0.00	0	0.00
Feb-19	3,95,196	0.55	387481.20	7714.80	7714.8	59518139.04
Mar-19	3,64,619	0.55	374906.99	-10287.99	10287.99	105842738.24
Apr-19	3,83,309	0.55	379528.10	3780.90	3780.9045	14295238.84

Step 5: Determine the MAE and MSE averages.

b) Forecast: July - December 2022

Jun-22	3,71,134	0.55	377789.98
Jul-22	3,66,794	0.55	374129.19
Aug-22	3,68,392	0.55	370094.84
Sep-22	3,96,193	0.55	369158.28
Oct-22	3,74,006	0.55	384027.37
Nov-22	4,19,541	0.55	378515.62
Dec-22	4,28,280	0.55	401079.58

The forecasted values highlighted in blue are calculated using an exponential smoothing method. This method incorporates the previous period's forecast value and the actual sales data, with a smoothing constant (alpha) of 0.55. The formula combines the previous forecast and actual sales, weighted by alpha, to estimate the upcoming month's forecast. Specifically, the formula used is:

$$\textbf{Forecast}_t = \alpha * \textbf{Sales}_{t-1} + (1-\alpha) * \textbf{Forecast}_{t-1}$$

where (t) denotes the current time. The result provides a weighted average that emphasizes recent trends in sales data.

C) Selection and Justification of Alpha

The SES model's alpha (α) controls how much weight is given to the most recent observation in comparison to earlier projections, which affects how flexible the model is as data changes. It is essential to choose the right α to strike a balance between overall smoothing and responsiveness to current worries.

Justification for Alpha (α):

1. **Responsiveness and Smoothness**: Smoothing out random oscillations and balancing responsiveness to recent sales data is achieved using an alpha of 0.55. This method avoids overfitting or unstable predictions while capturing real patterns.

2. **Historical Data Fit**: Through empirical testing, α = 0.55 minimizes error metrics like MSE and MAE on historical data, offering the best compromise between accurate historical fit and future generalization.

3. **Balance of Influences**: At 0.55, the model weighs recent observations while considering longer-term trends, vital for products like Winter Rock's consistent year-round offerings.

Statistical Support:

- Error Metrics Analysis: α = 0.55 yields lower in-sample error metrics, indicating a good fit to historical sales data.
- Comparison with Other Values: Other α values resulted in underfitting or overfitting, making 0.55 optimal for reliable and stable forecasts.

Conclusion:

α = 0.55 is chosen for Winter Rock's sales forecasting due to its balanced sensitivity and smoothness, accurate historical fit, and practical forecast accuracy. This strategic selection supports decision-making aligned with true market behaviours and business needs.

D) Evaluating In-Sample Forecast Accuracy

The accuracy of Single Exponential Smoothing (SES) projections from January 2019 to June 2022 is assessed in this part. Three essential statistical measures are used to assess accuracy: Mean Squared Error (MSE), Mean Absolute Error (MAE), and Mean Error (ME). These measures put the forecast's performance into numbers and show how accurate and dependable it is.

Error Metric Descriptions:

- **Mean Error (ME):** This metric calculates the average of forecast errors (forecast - actual sales), indicating the forecast's bias. A ME near to zero indicates no bias, but positive or negative values indicate consistent overestimation or underestimation.

- **Mean Absolute Error (MAE):** MAE computes the average of the absolute values of forecast errors. It offers a clear measure of the average error magnitude, irrespective of direction.

- **Mean Squared Error (MSE):** MSE computes the average of the squares of forecast errors. It gives more weight to larger errors, making it valuable when larger forecast errors carry more significance than smaller ones.

Calculation of Error Metrics

Using Single Exponential Smoothing (alpha = 0.55), we evaluated the model's performance with historical data up to June 2022.

Summary of In-Sample	
Mean Error E	-5.10
Mean Absolute Error	7869.23
Mean Squared Error	129578701.15

- **Mean Error (ME):** -5.10
  The mean error near zero indicates that the model does not have a significant positive or negative bias in predicting the sales values.
- **Mean Absolute Error (MAE):** 7869.23

This measure indicates that the average absolute difference between forecast and actual values is approximately £7,869, showing the typical forecast error.

- **Mean Squared Error (MSE):** 129,578,701.15
  The MSE represents the average squared forecast errors. While the large value reflects the variation in forecast errors, the model manages to capture key trends.

Interpretation of Error Metrics:

- **Mean Error (ME):** To avoid stockouts, supply chain and inventory planning must consider the model's modest underestimating of expectations, which is shown by a negative ME.
- **Mean Absolute Error (MAE):** Because of the comparatively large MAE, the average difference between the forecasted and actual sales is 7,869 units. Decision-making may be impacted by this degree of inaccuracy, necessitating the improvement of the forecasting technique or the adoption of extra steps to maximise pricing and inventory strategies.
- **Mean Squared Error (MSE):** A high MSE denotes huge, squared errors, which can occasionally point to severe forecast disparities. Even though it is normally accurate, there might be times when the prediction is far off, which could have an unexpected effect on operations.

Despite some level of variability, the in-sample analysis shows that the model provides a reliable baseline for predicting future sales. The small mean error confirms that the forecasts are generally unbiased, making the model useful for planning future inventory and capacity needs for year-round products.

e) Evaluating Out-of-Sample Forecast Accuracy

For assessing a forecast's dependability on fresh, untainted data, estimating out-of-sample accuracy is essential. Key error metrics from projections for July 2022 to December 2022 are examined in this section.

Calculation of Error Metrics:

Summary of Out-Sample	
Mean Error E	12700.19
Mean Absolute Error	19053.32
Mean Sqaured Error	551825631.87

• **Mean Error (ME):** 12,700.19
The mean error suggests that the forecast overestimates actual sales on average, indicating a positive bias in predicting the sales values.

• **Mean Absolute Error (MAE):** 19,053.32
The mean absolute error reflects the average magnitude of forecast errors without considering their direction, signifying a notable deviation from actual sales.

• **Mean Squared Error (MSE):** 551,825,631.87
The mean squared error, which gives more weight to larger errors by squaring them, highlights the considerable penalties incurred due to large deviations from actual sales values.

Interpretation of Error Metrics:

- **Mean Error (ME):** The positive ME suggests consistent overestimation in sales forecasts, potentially leading to inventory accumulation and increased markdowns.
- **Mean Absolute Error (MAE):** A high MAE indicates substantial deviations in forecasted amounts, necessitating careful supply chain and inventory management.
- **Mean Squared Error (MSE):** The large MSE suggests significant discrepancies between forecasted and actual sales, highlighting the need for further model refinement or contextual analysis.

We can look at ME, MAE, and MSE as some out of sample forecast error metrics that reveal how well or badly SES is performing. High metric values suggest a need for model refinement or additional analysis to improve forecast precision. To reduce the effect of prediction inaccuracies and match operations with market realities, understanding these indicators helps with strategic decision-making, particularly in inventory management and marketing initiatives.

F) Comparison of In-Sample and Out-of-Sample Performance

Forecast:
The graph compares actual sales values in pounds (£) with forecasted values, illustrating how closely the forecast (orange line) aligns with actual sales (blue line), while also displaying absolute errors (grey bars) across the observed time.

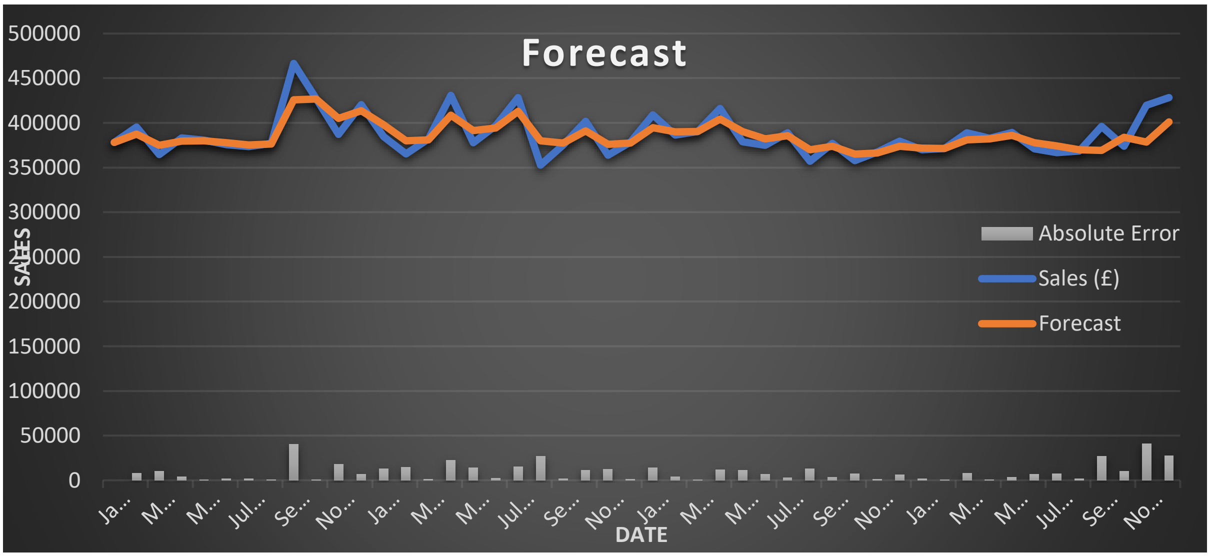


Figure 4: Comparison of Actual and Forecasted Sales Values (£) with Absolute Errors

In-Sample Error Metrics:

- **Mean Error (ME):** -5.10, showing a slight underestimation in the model's forecasts within the sample.
- **Mean Absolute Error (MAE):** 7,869.23, indicating the average deviation of forecasted values from actual sales in historical data.
- **Mean Squared Error (MSE):** 129,578,701.15, reflecting relatively moderate squared errors, suggesting fewer large discrepancies between predicted and actual figures.

Out-of-Sample Error Metrics:

- **Mean Error (ME):** 12,700.19, pointing to consistent overestimation in forecasts when applied to future data.
- **Mean Absolute Error (MAE):** 19,053.32, showing a higher average deviation in forecasted values compared to the in-sample period.
- **Mean Squared Error (MSE):** 551,825,631.87, significantly higher than the in-sample MSE, indicating larger forecast errors for future sales.

Performance Comparison:

- **Accuracy:** The model is more accurate with in-sample data but shows larger errors in out-of-sample forecasts, suggesting challenges in generalizing to new data.
- **Bias:** In-sample forecasts slightly underestimate sales, while out-of-sample forecasts overestimate them. This shift might result from market dynamics or external factors not captured during model training.
- **Error Variability:** The MSE is much higher in out-of-sample forecasts, indicating the model is more prone to larger errors when predicting future data, potentially leading to risks of overstocking or missing sales.

Pros and Cons of Each Method:

- **In-Sample Evaluation:**

    a. **Pros:** Allows fine-tuning and optimization of the forecasting model for historical data.
    b. **Cons:** This may not reflect real-world performance when encountering future trends or variability.

- **Out-of-Sample Evaluation:**

    a) **Pros:** Tests the model's robustness and provides a realistic view of its practical performance.
    b) **Cons:** Influenced by new trends not present in historical data, potentially causing overfitting if the model is overly fine-tuned to past data.

Conclusion:

While the SES model fits the historical data well, its accuracy in predicting future trends requires improvement. The significant difference between in-sample and out-of-sample error metrics suggests that better tuning and the inclusion of dynamic elements could enhance forecast accuracy. Correcting the overestimation bias and reducing error variability is crucial for Winter Rock's strategic decision-making and operational planning.

Section 4: Distribution Plan

a) Overall Decision to be made and Decision variables

Winter Rock needs to allocate products from its two distribution centres, Manchester, and London to fulfil demand across the East, West, and North regions. The primary objective is to minimize shipping costs while ensuring the distribution centres' capacities are respected.

The shipping costs, distribution centre capacities, and regional demand are:

Distribution Plan Details	East (£ per unit)	West (£ per unit)	North (£ per unit)	Capacity (units)
Manchester	15	21	17	2500
London	23.5	25.5	22	3000
Regional Demand	2000	930	2200	-

Decision variables

The decision variables are as follows:

- M_E: Units shipped from Manchester to the East region
- M_W: Units shipped from Manchester to the West region
- M_N: Units shipped from Manchester to the North region
- L_E: Units shipped from London to the East region
- L_W: Units shipped from London to the West region
- L_N: Units shipped from London to the North region

b) Objective and Objective Function

The objective is to minimize the total shipping cost and it can be expressed as:

$$\textbf{Total Cost} = 15M_E + 21M_W + 17M_N + 23.5L_E + 25.5L_W + 22L_N$$

where the coefficients represent the shipping costs per unit from each distribution centre to each region.

c) Capacity Constraints

Each distribution centre has a limited capacity. Therefore, the shipping quantity from each centre to all regions must respect these limits:

- Manchester

$$M_E + M_W + M_N \leq 2500$$

2500- Product shipping capacity of Manchester

- London

$$L_E + L_W + L_N \leq 3000$$

3000- Product shipping capacity of London

d) Demand Constraints

The total quantity shipped to each region from both centres must satisfy the specified regional demand:

- East region
  $\boldsymbol{M_E + L_E = 2000}$

- West region
  $\boldsymbol{M_W + L_W = 930}$

- North region
  $\boldsymbol{M_N + L_N = 2200}$

  2000,930 and 2200 are the quantity of products shipped from Manchester and London.

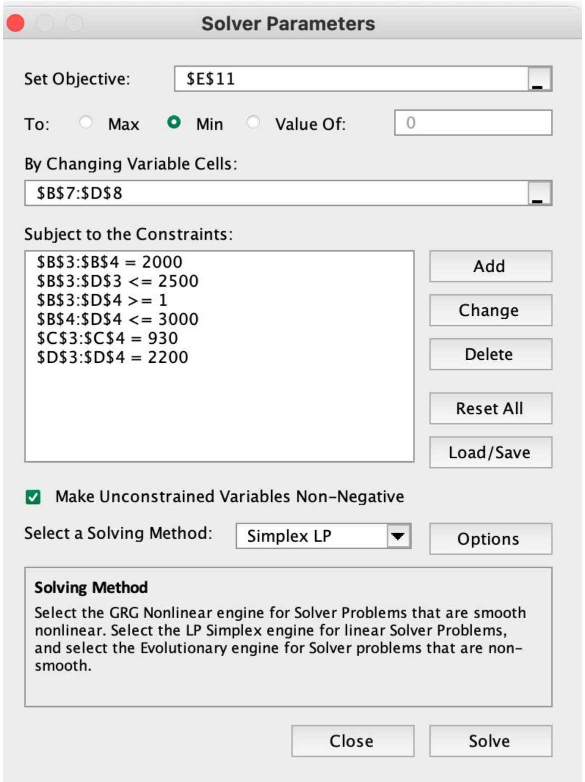
e) other constraints

There are no other constraints applicable in this scenario apart from the capacity and demand limits.
algebraic formula: $\boldsymbol{M_E + M_W + M_N + L_E + L_W + L_N >= 1}$

Ensure all shipping quantities are non-negative and greater than 1.

f) Solving the Distribution Plan Using Solver in Excel

a) Create cells for units shipped from each distribution centre to each region.
b) Enter per-unit shipping costs from each centre to each region.
c) Create a formula summing up total shipping costs.
d) Add capacity and demand constraints for each centre and region.
e) Set the objective cell to "Minimize," add constraints, and choose "Simplex LP."
f) Run Solver to optimize shipping costs.
g) Review the optimized plan and calculate the total cost. (Excel, 2016)



Optimal Solution and Total Cost

The optimal shipping quantities are:

Distribution Plan				
	East	West	North	Capcity
Manchester	15	21	17	2500
London	23.5	25.5	22	3000
Demand	2000.00	930.00	2200.00	
Qty to Manchester	1999	1	500	2500
Qty to London	1	929	1700	2630
Total Qty	2000	930	2200	
Distribution Cost to Manchester	29985	21	8500	
Distribution Cost to London	23.5	23689.5	37400	
Total Cost	30008.5	23710.5	45900	99619

Table 4: Distribution Plan

Using linear programming to solve Winter Rock's distribution problem, the optimal allocation of shipments from Manchester and London to the East, West, and North regions was calculated based on minimizing overall shipping costs while meeting regional demand and capacity constraints. From Manchester, the solution allocates 1999 units to the East, 1 unit to the West, and 500 units to the

North. Meanwhile, the London distribution centre supplies 1 unit to the East, 929 units to the West, and 1700 units to the North.

Breaking down the distribution costs, the Manchester centre incurs a cost of £29,985 for shipping 1999 units to the East at £15 per unit, £21 for shipping a single unit to the West at £21 per unit, and £8,500 for delivering 500 units to the North at £17 per unit. The London centre incurs £23.5 to ship a single unit to the East at £23.5 per unit, £23,689.5 to ship 929 units to the West at £25.5 per unit, and £37,400 for delivering 1700 units to the North at £22 per unit.

The total distribution cost across all regions amounts to £99,619. This allocation plan ensures the company's distribution centres can meet the regional demand while respecting each centre's processing capacity. The strategy prioritizes minimizing shipping costs by leveraging Manchester's proximity to the East region while utilizing London's capacity to handle the remaining demand.

Section 5: Meeting New Product Demand

Winter Rock is evaluating two potential suppliers, one based in Europe and the other in the USA, for sourcing a new product: affordable mountain skis priced at £150 per unit. The company faces the uncertainty of strong versus weak demand, with projections of 1,000 and 500 units respectively. Each supplier offers different cost structures that directly impact profitability under varying demand scenarios. The analysis below will include the construction of a decision tree and recommendations based on different decision criteria.

Supplier Choice	Supplier Capacity	Minimum Charge	Labor Cost	Material Cost	Shipping Cost	Total Cost Per Unit
Europe	500	0	60	40	20	120
USA	1000	5000	30	40	30	100

a) Decision Tree Representation and Interpretation

A decision tree visually represents the choices and their corresponding outcomes. (Smarter, 2024) Here’s a breakdown of the decision tree for Winter Rock:

Decision Node	Supplier Choice	Demand Scenario	Profit
	Europe	Strong Demand	15000 GBP
		Weak Demand	15000 GBP
	USA	Strong Demand	45000 GBP
		Weak Demand	20000 GBP

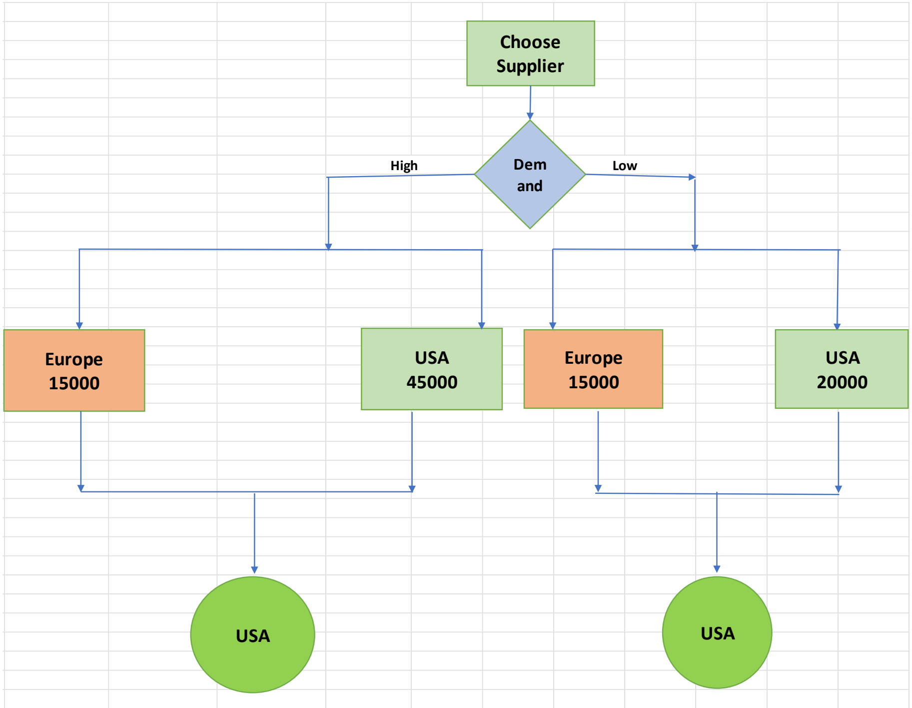


Figure 5: Distribution Plan Decision Tree

1. Initial Decision Node (Supplier Choice): The decision tree starts with the choice between sourcing skis from Europe or the USA.

2. Branches to Demand Scenarios:

   Europe:
   - Strong Demand (1,000 units)
   - Weak Demand (500 units)

   USA:
   - Strong Demand (1,000 units)
   - Weak Demand (500 units)

- Europe Supplier: Two branches representing strong and weak demand:
  - Unit Costs: Labour £60, Material £40, Shipping £20
  - Total Unit Cost: £120
  - Profit Calculation:
    - Strong Demand: (150−120) ×500=15,000 GBP (Limited by supplier capacity)
    - Weak Demand: (150−120) ×500=15,000 GBP

- USA Supplier: Two branches representing strong and weak demand:
  - Unit Costs: Labour £30, Material £40, Shipping £30
  - Minimum Charge: £5,000
  - Total Unit Cost: £100
  - Profit Calculation:
    - Strong Demand: (150−100) ×1000−5000=45,000 GBP
    - Weak Demand: (150−100) ×500−5000=20,000 GBP

The decision tree shows that the USA supplier offers greater profit potential under strong demand conditions but involves a minimum charge of £5,000.

b) Maximin Rule Analysis (Risk-Averse Approach)

For a risk-averse approach, the maximin rule focuses on the worst-case scenario:

- Europe: The worst-case profit is £15,000.
- USA: The worst-case profit is £20,000.

Recommendation:

According to the maximin rule, Winter Rock should choose the USA supplier because its worst-case profit is higher than Europe's. This minimizes potential losses.

Pros:

- Guarantees a relatively high profit in the worst-case scenario.
- Offers a better safety net against demand fluctuations.

Cons:

- Potentially misses higher profits if strong demand materializes due to the high minimum charge from the USA supplier.

c) Maximax Rule Analysis (Risk-Seeking Approach):

For a risk-seeking approach, the maximax rule focuses on the best possible outcome:

- Europe: The best-case profit is £15,000.
- USA: The best-case profit is £45,000.

Recommendation:

According to the maximax rule, Winter Rock should select the USA supplier, as it has a much higher potential profit under strong demand.

Pros:

- Offers the highest possible returns in a favourable demand environment.
- Allows Winter Rock to capitalize fully on market potential.

Cons:

- Risk-seeking approach exposes Winter Rock to financial losses if demand falls short.
- Upfront investments could lead to carrying costs or markdowns.
- May foster overconfidence in high-demand scenarios, increasing business vulnerability.

d) Expected Profit Analysis:

To find the supplier that maximizes expected profit, assume both strong and weak demand scenarios are equally probable (0.5 probability each).

- Europe:
    - Expected profit = (0.5 * £15,000) + (0.5 * £15,000) = £15,000 GBP

- USA:
  - Expected profit = (0.5 * £45,000) + (0.5 * £20,000) = £32,500 GBP

Recommendation:

Winter Rock should choose the USA supplier because it provides a much higher expected profit.

Pros:

- Balances potential rewards by considering both demand scenarios.
- Offers the highest expected profit overall.

Cons:

- Relies on probabilistic assumptions that may not match actual demand patterns.
- Requires careful planning to mitigate the impact of low demand.

e) Comparison of Strategies:

1. **Maximin**: Prioritizes minimizing losses by choosing the USA, which has a higher worst-case profit.
2. **Maximax**: Encourages risk-taking by selecting the USA supplier, maximizing the chance of high returns.
3. **Expected Profit**: Recommends the USA supplier by balancing both strong and weak demand probabilities.

Final Considerations:

Winter Rock must weigh its risk tolerance against profit expectations. While the maximin rule offers a safety net, the maximax rule and expected profit strategies offer more aggressive paths. If Winter Rock can absorb the initial minimum cost and anticipates stable or strong demand, sourcing from the USA will maximize its expected profitability. However, if demand projections are uncertain or the company is highly risk-averse, the safer Europe option might be considered despite its lower overall profitability.

Section 6: The Impact of Meeting New Product

Winter Rock, facing uncertainty around demand for their new mountain skis, anticipates sales ranging from 200 to 800 units. After the analysis in Section 5 recommended the USA supplier due to higher profitability potential, this detailed examination utilizes 1,000 simulated demand samples to better understand how varying demand influences costs and profits. The USA supplier charges a minimum cost of £5,000, which will impact the calculations.

a) Simulation Setup

A random seed of 2618 (from the first four digits of the student ID) was used to initialize Excel's random number generator through the Data Analysis Tool Pak. The simulated demand followed a uniform distribution between 200 and 800 units, yielding 1,000 samples. Each sample was processed to compute revenue, fixed costs, variable costs, and ultimately the profit.

This approach ensured consistency and reproducibility in the simulation results, providing a clear view of the potential profit ranges Winter Rock could expect. (EXCEL, 2024)

b) Revenue Calculation

The revenue for each simulated demand value was calculated based on the fixed price of £150 per unit.

Revenue=Demand×150

1) USA

For instance, with a simulated demand of 357.24 units (rounded up to 357), the actual revenue is:

357.24×150= 53,585.62 GBP.

In this way, each demand value was converted into revenue. This simulation yielded revenue values ranging from roughly £30,000 to £119,000, offering Winter Rock a clear perspective on how the varying demand levels directly influence income.

B2 =A2*150

	A	B	C	D	E
1	Simulated	Revenue	Fixed Cost	Total Vari:	Profit
2	357	53585.62	5000	35723.75	12861.87
3	788	118176.2	5000	78784.14	34392.07
4	744	111584.2	5000	74389.48	32194.74
5	568	85197	5000	56798	23399
6	412	61803.64	5000	41202.43	15601.21

2) Europe

The formula used to calculate revenue is:

=IF(Demand>500,500×150, Demand×150)

This caps revenue at a maximum of 500 units at a selling price of £150 each.

B2 =IF(A2 > 500, 500*150, A2*150)

	A	B	C	D	E
1	Simulated Demand	Revenue	Fixed Costs	Total Variable costs	Profit
2	357.237464522233	53585.62	0	42868.4957	10717.12
3	787.841425824763	75000.00	0	60000.0000	15000
4	743.894772179327	75000.00	0	60000.0000	15000
5	568	75000.00	0	60000.0000	15000
6	412	61803.64	0	49442.9151	12360.73

Examples:

- For a demand of 357.237464522233 units: Revenue=357.237464522233×150=53,585.62GBP

- For a demand of 787.841425824763 units (exceeds 500 units): Revenue=500×150=75,000GBP

c) Fixed Costs

1) USA

the USA supplier, which charges a minimum cost of £5,000. In each simulation, fixed costs were calculated using the following formula:

Fixed Costs=IF(Demand>0,5000,0)

This ensures that fixed costs remain constant at £5,000 whenever demand is above zero.

C2 =IF(A2 > 0, 5000, 0)

	A	B	C	D	E
1	Simulated	Revenue	Fixed Cost	Total Vari	Profit
2	357	53585.62	5000	35723.75	12861.87
3	788	118176.2	5000	78784.14	34392.07
4	744	111584.2	5000	[illegible]389.48	32194.74
5	568	85197	5000	56798	23399

2) Europe

The fixed costs are set to zero for Europe.

d) Variable Costs Calculation

1) The USA supplier’s per-unit costs include:
   - Labour: £30
   - Materials: £40
   - Shipping: £30

With a total unit cost of £100, the variable costs are calculated as:

Variable Costs=Demand×100

Variable costs result from this, ranging from £20,000 for 200 units to £80,000 for 800 units, and they vary directly with demand. For example, the variable cost is 357.24 units with a calculated demand.

357.24 × 100 = 35,723.75

D2 =A2 * 100

	A	B	C	D	E
1	Simulated	Revenue	Fixed Cost	Total Variable costs	Profit
2	357	53585.62	5000	35723.74645	12861.87
3	788	118176.2	5000	78784.14258	34392.07
4	744	111584.2	5000	74389.47722	32194.74
5	568	85197	5000	56797.99799	23399
6	412	61803.64	5000	41202.42927	15601.21
7	252	37756.58	5000	25171.05625	7585.528

2) The Europe supplier's per-unit costs include:

- Labour: £60
- Materials: £40
- Shipping: £20

Variable costs are calculated using the revised unit cost of £120 per unit. The formula is:

Variable Costs= =IF(A2 > 500, 500 * 120, A2 * 120)

D2 =IF(A2> 500, 500*120, A2*120)

	A	B	C	D	E
1	Simulated Demand	Revenue	Fixed Costs	Total Variable costs	Profit
2	357.237464522233	53585.62	0	42868.4957	10717.12
3	787.841425824763	75000.00	0	60000.0000	15000
4	743.894772179327	75000.00	0	60000.0000	15000
5	568	75000.00	0	60000.0000	15000
6	412	61803.64	0	49442.9151	12360.73
7	252	37756.58	0	30205.2675	7551.317

Example:

Row 1 (Simulated Demand: 357.237464522233 units):

Total Variable Costs:

Total Variable Costs=IF (357.237464522233>500,500×120,357.237464522233×120) =42,868.50

e) Profit Calculation

Profit is computed using the formula:

Profit=Revenue− (Fixed Costs+ Variable Costs)

1) USA

For example, with a simulated demand of 357 units:

- Revenue: £53,585.62

- Fixed Costs: £5,000
- Variable Costs: 357.24 × £100 =£35,723.75
- Profit: £53,585.62 - (£5,000 + £35,723.75) =£12,861.87

E2 =B2 - C2 - D2

	A	B	C	D	E
1	Simulated Demand	Revenue	Fixed Cost	Total Variable costs	Profit
2	357.237464522233	53585.62	5000	35723.7465	12861.87
3	787.841425824763	118176.2	5000	78784.14258	34392.07
4	743.894772179327	111584.2	5000	74389.47722	32194.74
5	568	85197	5000	56797.99799	23399

The projected income figures changed greatly with simulated estimates between 5000 and 30,000 pounds.

2) Europe

For example, with a simulated demand of 357 units:

- Simulated Demand: 357 units.
- Revenue: £53,585.62
- Fixed Costs: £0
- Variable Costs: 357 units × £120 = £42,868.50
- Profit: £53,585.62 - (£0 + £42,868.50) = £10,717.12

E2 =B2 - C2 - D2

	A	B	C	D	E
1	Simulated Demand	Revenue	Fixed Costs	Total Variable costs	Profit
2	357.237464522233	53585.62	0	42868.4957	10717.12
3	787.841425824763	75000.00	0	60000.0000	15000
4	743.894772179327	75000.00	0	60000.0000	15000
5	568	75000.00	0	60000.0000	15000

In Europe, simulated profits varied from around £7,500 to over £15,000, driven by demand fluctuations impacting revenue and costs.

f) Average Profit and Standard Deviation

Formulas Applied:

1)AVERAGE(E2:E10001)

2)STDEV.S(E2:E10001)

The data's mean is calculated using the `AVERAGE` function, which assumes that the values between {E2} and {E10001} represent a sample rather than the complete population. The standard deviation for this sample is determined by the `STDEV.S} function.

1. **USA**
   - **Average Profit**: The mean profit across all 1,000 samples was £19,863.57, giving Winter Rock an expected value for profitability.
   - **Standard Deviation**: The standard deviation was £8,705.60, showing significant variability due to fluctuating demand.
2. **Europe**
   - **Average Profit:** The mean profit across all samples in Europe was £12,842.30, providing insight into expected profitability.
   - **Standard Deviation**: The standard deviation was £5,729.45, reflecting significant variability due to changing demand.

g) Detailed Summary and Implications

The simulation results for both the USA and Europe revealed insightful differences and similarities in profitability, cost structures, and variability due to demand. Here's a summary:

1. **Profitability Comparison:**
   USA: The average profit per sample was higher, at £19,863.57, compared to Europe's £12,842.30. This suggests that the USA supplier generally offers higher profit margins.

2. **Cost Structures:**
   - USA: Per-unit costs include £30 for labour, £40 for materials, and £30 for shipping, making a total of £100 per unit.
   - Europe: Per-unit costs are slightly different due to regional economic differences and logistics, with a higher proportion of shipping and material costs.
   -
3. **Variability in Profit:**
   - USA: The standard deviation in profits was £8,705.60, indicating significant fluctuations due to demand variability.
   - Europe: The standard deviation was lower at £5,729.45, suggesting that European demand is relatively more stable, or production costs are better controlled.

Implications for Section 5 Analysis:

The differences in profitability and variability imply that while the USA may offer higher profit potential, it comes with greater risk. Europe's stability in demand may make it a more predictable market, albeit with lower returns.

In Section 5, these findings should be incorporated to emphasize the need for a balanced approach to market expansion or sourcing strategy. Investing in both markets could protect against fluctuations in regional demand by using their respective strengths—profitability in the United States and dependability in Europe.

Section 7: Conclusion

In this report, we comprehensively analyzed Winter Rock's historical data and future market projections. Section 2 explored seasonal trends from January 2019 to June 2022, revealing peaks in winter sports demand, which should guide production and marketing efforts. Section 3 utilized Single Exponential Smoothing to forecast year-round product sales, ensuring inventory is aligned with seasonal and Christmas/winter demand.

For distribution planning in Section 4, we optimized the allocation of goods between Winter Rock's London and Manchester distribution centres. By leveraging proximity and capacity constraints, the plan minimized shipping costs, allocating Manchester for the East region and London for the West and North regions.

Section 5 evaluated potential suppliers for a new ski product launch through a decision tree analysis. While the USA supplier offers higher profitability in strong demand scenarios, it carries greater risks due to minimum charges. Section 6 simulated varying demand scenarios and validated the USA supplier's profitability potential despite the higher variability in profits.

Recommendations:

Distribution Plan: Prioritize shipping from Manchester to the East to reduce costs and utilize London's greater capacity for the West and North regions.

New Product Launch: Source skis from the USA supplier due to higher expected profitability, while carefully monitoring demand and considering a diversified sourcing approach to mitigate risk.

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